Using Adaptive Agent-Based Simulation Models to Assist Planners in Policy Development: The Case of Rent Control

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USING ADAPTIVE AGENT-BASED SIMULATION MODELS TO ASSIST PLANNERS IN POLICY DEVELOPMENT: THE CASE OF RENT CONTROL

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Abstract:[2] Computer simulation modeling for policy development in planning has had difficulty gaining a consistent foothold. Reasons for this include bad experiences with large-scale, comprehensive models (e.g., Forrester, 1969) and the lack of theory that one can quantify (Batty, 1994). Batty (1994) has suggested that new types of computational models, based on the tenets of complexity theory (Bernard, under revision) may prove useful. One type of complexity theory model is an "adaptive agent based model" in which the actions, interactions, and adaptations of many autonomous, heterogeneous "agents" (households, firms, etc.) produce emergent, system-wide behavior. One can examine this emergent behavior using commonly employed metrics, but one can also garner a richer, more intuitive understanding of how the individual behavior of the agents self-organize to produce the entire system. Using this type of modeling for small-scale planning problems can both inform planning theorists and improve planning practice by providing rich understanding that standard quantitative models do not. In this paper, I will present an agent-based model of rent control. Household agents (with different income levels) rented apartments from landlord agents – these apartments were situated on a lattice. Landlord agents continually adapted to the conditions of the marketplace (apartment demand, type of rent control in place, and so on), raising and lowering their prices as they saw fit. I varied conditions of rent decontrol and measured various metrics, such as vacancy rate, apartment quality, tenant income, and average rent paid. I found that a market with rent control typically has tenants with lower incomes than a non-rent controlled market, even substantially after the market has been suddenly decontrolled. In addition, I found that there were lower vacancy rates in regimes of rent control. As these results are not based on actual data, they are merely presented as suggestive. In fact, the point of abstract computational models such as the one presented here is not as the ultimate predictors of policy decisions, but as tools to inform and provoke discussion among policy makers. Thus, I will conclude by speculating on the use of adaptive agent-based models for assisting in policy formulation.

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INTRODUCTION

Urban and regional planning has relied upon demographic and economic forecasts to guide policy development and provide estimates of travel demand for road construction. These forecasts have typically relied upon standard statistical forecasting techniques such as linear regression or maximum likelihood coefficient estimation of a fixed model structure. Evaluating the accuracy of these forecasts is not common, as they sometimes range 30 years into the future, and new forecasts for metropolitan areas typically have been produced every three to five years. With the ubiquitous increase of hardware speed and software sophistication, a new method of forecasting has emerged -- adaptive agent-based simulation. This method has the potential of revolutionizing the planning and policy development field.

In this paper, I will first outline how computer models have been used in urban and regional planning and policy development. Then, I will discuss new ways of using models to assist in policy development through adaptive agent-based simulation modeling. Next, I will introduce a model of rent control and discuss preliminary results of the model. Finally, I will conclude with thoughts on how such models can be used practically in professional planners' offices.

The goal of this paper is simple. I hope to show how adaptive agent-based simulation modeling is a new and useful technique for doing policy simulation in planning, and provide a simulation of rent control as one such example. Although I discuss rent control and its literature, I do not formally present research hypotheses from the literature and then attempt to disprove them – I will do that in Bernard (forthcoming). Instead, the discussions of rent control are merely presented as a context within which to discuss agent-based modeling and policy simulation.

COMPUTER MODELS IN PLANNING

In this section, I will discuss a brief history of computer models in planning and then develop the idea that such models have evolved such that they can now be used to simulate the effects of policy decisions.

A BRIEF HISTORY

Models in planning and policy development have had a turbulent history. Once hailed as the saviors of cities due to their comprehensive goal to predict the future of many aspects of an area, they were eventually seen as failed examples of modernism's totalitarian regime. There have been many attempts at creating large-scale urban models including the early linear programming work of Herbert and Stevens (1960) for allocating households to residential locations, through the Lowry (1964) model based on export base theory, the highly disaggregated EMPIRIC (Hill, Brand, and Hansen, 1965), the model of the Detroit housing market NBER (Ingram, Kain, and Ginn, 1972), as well as MEPLAN (Hunt and Simmonds, 1993). Early on, Lee (1973) recognized seven sins that many of these models committed, and his paper caused the developers of these models to go almost underground in their model development.

Nevertheless, computer models are used to forecast demographic, economic, and land use changes in many metropolitan areas throughout the world. In fact, some measure of standardization has emerged in the United States, in which the Lowry–derivative DRAM/EMPAL component of the ITLUP model (Putman, 1991) is used in over a dozen metropolitan areas. A different disaggregated approach is in the CUFM model (Landis, 1995), which models the northern California bay area. Interestingly, there are many different research programs to develop these models further throughout the world; Wegener (1994) provides a relatively current review of these research programs.

POLICY SIMULATION

Predictions of precisely what will happen in an area are, in some ways, not entirely useful. Such a prediction presumes that no matter what the planner does to counteract or encourage aspects of the prediction, it will not matter, because the future is preordained, as it were. What would be more useful is a prediction based upon one or more initial scenarios (e.g., low growth or high growth) that the planner creates. In this case, the future is dependent upon the implementation of one of these scenarios. Even more useful would be the ability to dynamically change policy midstream – when the simulation is in the process of running. Such "policy simulation" would be useful for any number of purposes.

This idea is not new, of course. In a highly influential book, Forrester (1969) tried many different types of policy simulation using his Urban Dynamics model. This model simulated a highly abstract (and spatially undifferentiated) fictional city. Forrester did not calibrate this model will any real data – instead he simulated the city's development starting from an empty spatial plane and allowed it to grow into a mature and ultimately stagnant city in a state of equilibrium. *Levels* of many different variables, such as "luxury housing stock" and "underemployed arrival rate", were measured in response to different policies (such as a "low income job program"). Forrester built Urban Dynamics using a systems dynamics approach; mathematical equations calculated the change of these variables' *levels* that fluctuated according to *rates* of change that were these equations' coefficients. Some people reviled the model because the policies that it demonstrated as being best for a city were somewhat reactionary.

A system dynamics approach, in which levels of variables are controlled by the rates of change of other variables, is very useful is simulating many systems. Yet, such a system will ultimately fail when attempting to tackle the myriad interactions that comprise the development of a metropolitan area, in which the units that interact in that city adapt to the continual changes in the environment. Instead, a model that attempts to capture these interactions, at least in part, will have a better chance of demonstrating the possible results of policy changes. Adaptive agent-based simulation modeling is one such system.

Policy simulation, as I conceive it, is not a normative prescription for what will happen in a particular region. Instead, it is a technique designed to generate ideas a facilitate discussion among decision-makers. Like a spreadsheet, a computer takes in data, processes it, and presents it in a numeric, graphical, or visual format. Although the results that it produces are suggestive, not necessarily predictive, it still provides a frame of reference for meaningful dialogue.

Policy simulation as done on a computer has a chance to provide counterintuitive or unexpected insights. As there are usually many different processes at work, there is a chance that the model may produce unforeseen possibilities or unintended consequences. Finally, as the designer or programmer can change the model at any moment, any assumptions can be altered to suit perhaps politically opposed factions. Indeed, Klosterman (1987) suggests that rival political groups may use competing models to forecasting purposes as a catalyst for constructive dialogue.

ADAPTIVE AGENT-BASED MODELS

In this section, I describe how a new type of simulation modeling, adaptive agent-based models, take a much different approach to modeling an area than traditional numerical techniques. Certainly, adaptive agent-based models share some traits with standard systems dynamic models (e.g., Forrester, 1969) – they are both data intensive and have many free parameters – but, adaptive agent-based models differ significantly. Table 1 presents a comparison between the standard models and new types of models, of which adaptive agent-based modeling is one.

TRADTIONAL SIMULATION	**AGENT-BASED SIMULATION**
Deterministic (one future)	Stochastic (multiple futures)
Allocative (top-down)	Aggregative (bottom-up)
Equation-based formulas	Adaptive agents
Do not give explanations	Explanatory power
Few parameters	Many parameters
Environment given	Environment created
You can REACT to them	You can LEARN from them

Table 1: Comparison of current and new models

First, traditional simulation in planning is a deterministic enterprise. These simulation models gave only one answer – "the future will be X". Agent-based simulation differs in that the models are stochastic; there is an element of randomness involved. The models do not presume that they can precisely predict what will happen in the future; instead, they can be run several times, and the predicted future is likely to be different each time.

Second, traditional simulation in planning is allocative. A larger "control total" is given to the model, such as the population of the entire region, and the simulation model allocates pieces of that entire total spatially to different areas. Agent-based simulations are aggregative; they predict changes at a micro level and then sum the micro changes to reach a larger total. This is the standard top-down versus bottom-up conflict.

Third, and most important, the units of analysis in the agent-based models are not ecologically fallacious quantities such as "worker stock". Nor are these quantities directly related to one another directly in a closed form equation. Instead, the units of analysis in adaptive agent-based models are typically the individual units that make up the crux of the system. Adaptive agent-based modeling attempts to directly replicate the interactions and/or decision processes of these individuals in an environment, whether these individuals are cells, animals, people, or households – in planning, those units consist of individual households or persons. Non agent-based models have the characteristic of using data from crosstabulations – data such as the number of older men that live in nursing homes. Analysis for these models (such as predicting the migration rate from the non-nursing home male population to those who live in nursing homes) is done using that particular number. An agent-based model, on the other hand, might instead try and replicate the decision processes of each individual family associated with each older man in that category. The agent-based model might predict, given the family's income level, social status, and cultural belief system, the chance that a man in that family will move into a nursing home. Furthermore, agents are typically adaptive in that they remember events and can learn from experience. Therefore, an agent might not react the same way if presented with the same situation twice. Adaptation in a system causes fundamental changes in the way the system operates.

Fourth, traditional simulation does not give the user much in the way of explanation. As traditional models are equation-based, their method of explanation succumbs to discussions of correlation and causation issues – alternately, the equation may not make much sense intuitively, but it works, and thus it is used. Agent-based models, however, allow the researcher to trace back the causes of individual decisions made by particular agents and diagnose that agent's decision process.

Fifth, being able to diagnose something in an agent's decision process requires a vast number of parameters in an agent-based model. This is in direct contrast to a traditional simulation model, in which researchers attempt to constrain the number of parameters to a reasonably small number.

Sixth, the environment in traditional simulation is usually given, and strict assumptions are placed on it. Since agent-based modeling is bottom-up, however, and agents adapt and learn, the environment in which they operate constantly changes. Therefore, the environment in an agent-based model is created by the actions of the agents – indeed even in some simulations, the agents may be able to modify the assumptions originally placed on the model itself.

Seventh, you can react to the results from a traditional simulation model, as sometimes the model can be a highly nonlinear structure that is difficult to understand, even for sophisticated mathematicians (e.g., see Putman, 1991). With its ability to provide explanations, multiple futures, and dynamic environment, you can learn from an agent-based model much more easily.

For example, suppose you were building a predictive model of travel demand. You might set up a road network assigning nodes and links. You might get traffic counts on these major links, and then calibrate a complex mathematical formula to predict how travel time might change if you were to delete or add a link.

With an agent-based model, you might also construct a road network, but then you might collect data from each entry point about drivers' behavior, their psychology, and driving habits (what road they take, what happens if there's an accident, etc.). Then, you would simulate each day by attempting to replicate the behavior of each individual driver on the road – exactly where that driver is, what that driver is thinking, how fast that driver is driving, and so on. Then, you add or delete roads in your network to see what might happen. A very similar simulation actually exists today (Nagel and Paczuski, 1995).

Although I do not plan to discuss data in any detail, in most cases, loading of data into these models is difficult, if not impossible. The data on individuals either does not exist or is protected by privacy concerns. Nevertheless, with well-designed surveys and matching techniques from demographic and economic characteristics, a reasonable sized sample of individuals can provide data for a large number of these adaptive agents.

AN ADAPTIVE AGENT-BASED MODEL OF RENT CONTROL

In this section, I explain an application of adaptive agent-based simulation modeling – one that simulates a rent control market in a highly abstract city.

BRIEF OVERVIEW OF RENT CONTROL

Traditionally, economists have thought rather poorly of rent controls. Many think of rent control as consisting of setting a maximum price for an housing unit above which rents cannot rise; these controls have been called first generation controls. Standard economic treatises of rent controls have generally found these first generation rent controls to be bad for all parties. Fallis and Smith (1984), for instance, said that in a rent-controlled market, apartment price of uncontrolled apartments would increase at a rate greater than controlled apartments. Olsen (1972) used a regression model to claim that rent control cost landlords more than it benefited tenants; in addition, he claimed that tenants in controlled housing consumed less "housing services" and non-housing goods that they would have, had they been in uncontrolled housing stock.

Skaburskis and Teitz (1998) provided a good summary of what the rent control literature (primarily in economics) has stated to be the deleterious effects of rent controls. These include: landlords cutting back on maintenance; quality of the rent controlled apartment decreases; development of new housing declines; more home ownership and thus, reduced rental stock and a tighter market; reduced movement out of each apartment even during life cycle changes; and, reduced in-migration to the city due to the high costs of uncontrolled apartments and low vacancy rates.

The disgruntlement with first generation rent controls has been ameliorated somewhat by newer "second generation" controls. Second generation rent controls are less drastic than first generation rent freezes. Second generation controls usually allow a small percentage increase of the rent each year. Other possible increases can be allowed for unforeseen cost increases to the landlord, hardship provisions, or rate of return provisions (neatly summarized by Keating, 1998). Arnott (1995), however, claims that views on rent control have been changing recently, and that economists are now more willing to accept modest second generation controls.

THE MODEL

In this section, I describe the adaptive agent-based simulation model of rent control. Although this description highlights the important aspects of the of the model, to be comprehensive such that a researcher would be able to replicate its results would require a level of detail insufficient for a paper of this size. Still, a comprehensive description of the model will be available in the future (see Bernard, forthcoming).

REPRESENTATION OF THE CITY

I conceive that the rental housing market has one major type of object, apartments, and has two major players, the apartment renters and the landlords; all are represented explicitly in the model. Apartment brokers and/or real estate agents were not explicitly represented in the model.

The simulated housing market was represented spatially on a 10 by 10 lattice, with one apartment per cell; thus, there were 100 apartments in the housing market. The central desired location that all renters wanted to be close to was cell (3,4) -- the third row and the fourth column from the upper left.

Each iteration of the simulation model was one simulated month. I chose this time frame, as it is the typical time frame that people make rent payments.

When rent controls were instituted, each apartment that has an assessed value above the average has a 60% chance of being rent controlled. This control was a simple second-generation control that allows rents to be raised 2% per year.

Sudden decontrol removes all rent control immediately. Luxury decontrol decontrols every controlled apartments in which the renter has a budget above the average for those living in controlled apartments (thus, approximately half of all controlled apartments).

APARTMENTS

Only one renter could occupy each apartment. All apartments were homogenous in terms of their level of housing service offered – they fundamentally differed from one another only in their location on the lattice and their quality. In metaphorical terms, all apartments were identical regarding the number of bedrooms, the lighting, the appliances, the utilities, and so on, but their location in space varied, and the quality of each identical apartment varied.

Regarding the quality, each apartment had a particular quality value associated with it, which declined gradually over time, unless a landlord performed maintenance on the apartment.

Specifically, for a particular apartment, it has an associated quality q,

$$q \in [0..\infty]$$

quality varies between 0 and positive infinity. Furthermore, quality degrades at a multiplicative rate, specifically,

$$q_{t+1} = \delta q_t$$

where δ is fixed at $0.5^{1/12}$. This means that apartments will degrade to approximately one-half its quality value in a year of simulated time. If a landlord raises the proposed price on an apartment, the landlord will also increase the quality of the apartment,

$$q_{t+1} = q_t + \sqrt{p_{t+1} / p_t}$$

where q is quality, p is price or proposed price, and t is the iteration.

Each apartment is on a twelve-month lease cycle. Renters had no choice but to accept a 12 month commitment to live in an apartment.

RENTERS

Each renter in the market was a utility-maximizing individual, subject to individual budget constraints. The renter chose an apartment based on the following specific utility function,

$$U_{i,j} = \alpha_j f_Q(q_i) + \beta_j f_D(d_i, \Lambda) + \gamma_j f_P(p_i, b_j)$$

where $U_{i,j}$ is the utility of renter j of apartment i, $f_{Q/D/P}$ are specific functions of *Q*uality, *D*istance, and *P*rice respectively, q_i is apartment quality, d_i is the apartment's Euclidean distance from a central location Λ, p_i is apartment price, b_j is the budget of renter j, and α_j, β_j, and γ_j are free coefficients. The functions follow.

$$f_Q = -1 + 2\left(\frac{e^{q_i}}{1+e^{q_i}}\right)$$

$$f_D = \sqrt{\frac{1}{1 + \|d_i, \Lambda\|}}$$

$$f_P = \frac{\ln\left(1 + \left(b_j - p_i\right)\right)}{\ln\left(1 + \left(b_j - p_i\right)\right) + 1}$$

Note that each function scales its results between 0 and 1.

For the experiments described below, each renter had homogenous preferences between the quality, distance, and price functions. Specifically,

$$\forall i, \alpha_i = 0.4; \beta_i = 0.3; \gamma_i = 0.3$$

When searching for an apartment each renter did not have perfect knowledge of what apartments were available – renters were only able to look at three apartments on the advertising list. Also, whenever a renter searched for an apartment, they were assessed a search cost equivalent to 12% of the eventual cost of renting the apartment. Such a search cost was reflected in the each renter's assessment of the price of the apartment (i.e., price was increased in the utility equation by 0.12).

At the end of each lease term, there was a 2% chance that each renter would leave the market.

LANDLORDS

There were 100 landlords in the market, each one associated with a particular apartment. Landlords were price setters on their apartments. Landlords have no knowledge of any renter's budget or preferences.

The landlords' major action is to set the price on the apartment. Price for the next lease cycle is only set when either (1) the apartment has two months remaining on its lease, or (2) the apartment is vacant. The landlords have two variables that are related to its price setting behavior: *r*, the "raise rate", and *l*, the "lower rate". In addition, the landlords know about the assessed values of the four (or three or two, if it is on an edge or corner) neighboring apartments (i.e., its Von Neumann neighborhood). Specifically, the landlords use the following set of rules.

A. If the apartment is vacant, set the "adjust rate" to the "lower rate"

B. If the apartment has two months left on the lease, set the "adjust rate" to the "raise rate"

C. If the apartment is rent controlled, set the "adjust rate" to the maximum allowable rate

D. Change the price of an apartment by adding the "adjust rate" times the average of the old price and the assessed value of the apartments neighbors

The landlords also learn about the changing environment and when it is better to raise or lower prices – thus every landlord is adaptive. Generally, the following concepts governed the landlords' price setting:

- if its current renter renewed its lease, then increase "raise rate"
- if its current renter did not renew its lease, then decrease "raise rate"
- if another renter rented the apartment, then increase "lower rate"
- if the apartment is still vacant, then decrease "lower rate"

The landlords are able to distinguish between these cases by examining how many months left in the current lease. If there are 13 months left in the lease, it indicates that a renter just renewed its lease (i.e., there was one month left, and then the renewal, and so add twelve months to make thirteen). In this case, the raise rate is adjusted as follows:

$$r_{t+1} = r_t + 0.05(1 - r_t)$$

If there is 1 month left in the lease, it means that the current renter did not renew its lease. In this case, the raise rate is adjusted as follows:

$$r_{t+1} = r_t - 0.06(r_t)$$

If there are 12 months left in the lease, it means that a new renter took the apartment. In this case, the lower rate is adjusted as follows:

$$l_{t+1} = l_t - 0.03(l_t)$$

If the apartment is vacant, the lower rate is adjusted as follows:

$$l_{t+1} = l_t + 0.025(-0.5 - l_t)$$

The parameters and coefficients of these learning equations were determined through trial and error.

If an apartment is advertised for rent, its advertisement (location, price, and quality) is posted to a list to which renters have access.

OTHER VARIABLES

The advertising medium in which communication between landlords and renters takes place is a simple list. The list did not clear every simulated month.

I represented the economy as inflationary. Inflation in the economy was fixed at a Y_0 annual increase currently (.04 or 4% per year) and reflected in the available budget that each renter had to spend on housing costs. Note that the equations presented above (especially the equations that include price), the prices and budgets were assumed to be inflation adjusted.

INITIAL STATE

The initial state of each simulation was as follows.

Parameters for the renters' utility functions were set as described above.

Renters' budgets were determined by the following equation,

$$b = 1 + (0.4 + \Xi[0.0..0.6])^4 P_0$$

where P_0 is the initial maximum possible rent in the market (set to 200) and where Ξ[x…y] is a random number drawn from a uniform distribution that ranges from x to y. Note that this equation provides a distribution of positively skewed incomes.

A renter occupied each apartment. Each renter's remaining months left on the lease was a randomly drawn integer from a range of 1 to 13.

The rent the tenant pays and price charged for the apartment was a function of its budget. Specifically,

$$p_i = (0.7 + \Xi[0.0..0.3])b_j$$

The assessed value of the apartment was set to the current rent.

Landlords initial raise rate, r, and lower rate, l, were set to -0.02 and +0.10 respectively, for all landlords.

MODEL PROCESS FLOW

The rent control simulation model followed a specific flow of information each iteration. Figure 1 graphically displays the process flow of the simulation model.

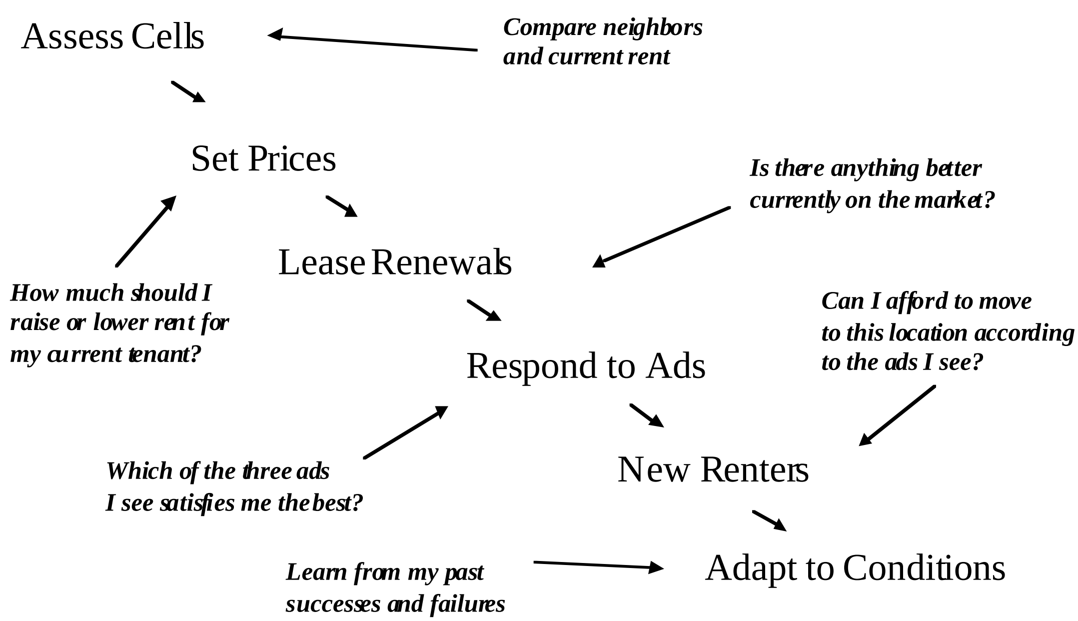

Figure 1: Process Flow of the Rent Control Simulation Model

ASSESS CELLS

Each iteration, the simulation applied an assessment function to all apartments in the lattice. This assessment function examined each apartment in the lattice and used a combination of the current rent of uncontrolled neighboring apartments and the apartment's current assessment to arrive at an assessment.

Specifically, each uncontrolled apartment's assessment is the average of its current rent and last month's average assessment of its uncontrolled neighbors. If the apartment is controlled, its assessment is the average of its last month's assessment and last month's average assessment of its uncontrolled neighbors.

SET PRICES

Each landlord then sets the price of its apartment. This price setting procedure has been described above.

LEASE RENEWALS

Renters whose apartments have two months remaining on their leases decide whether to leave the market. If they do not, then they decide whether or not to renew their current lease. They examine three advertisements (chosen randomly) on the advertisement list and see if any of these apartments would given them higher utility (with the included search cost). If so, they do not renew their lease. If not, they do renew their lease.

RESPOND TO ADS

All renters who have one month remaining on their lease then choose a new apartment. In random order, each renter examines three ads from the list. The renter then chooses that ad that gives the highest utility and leases that apartment. If the price of all three apartments that renter chose is greater than the renter's budget, the renter leaves the housing market.

NEW RENTERS

Each month, I represented adaptive exogenous simulated demand for apartments in the city. Each month, there was a chance that a potential renter from outside the area would initiate a search process for an apartment in the city. If that renter found an acceptable apartment, another renter would immediately search for an apartment in city. If that new renter found an apartment, with an even greater chance another renter would look for an apartment, and so on.

The initial percentage chance that a new renter would enter the market was 70%. The adjustment for a successful search or unsuccessful search was raising or lowering the rate 1% respectively.

New renters were set with the same preferences on utility equations. New renters' budgets were set to

$$b = 1 + \left((1 + Y_0)^{\left(t/12 \right)} \right) (0.4 + \Xi[0.0..0.6])^4 P_0$$

Note that this equation has the effect of having budgets slightly less than what the average budget in the town is expected to be, given the inflationary economy. Also, the distribution from which the new renter's budget is drawn is positively skewed.

ADAPT TO CONDITIONS

Finally, the landlords examine what happened in their apartments that month and adjust their learning parameters accordingly.

EXPERIMENTAL DESIGN

I ran each simulation run for a total of 750 simulated months. In the first 250 months, there was not any rent control in effect. At month 251, I either enacted a regime of rent control or did not activate any controls. The rent control regime consisted of a typical second-generation rent control in which landlords were only allowed to raise prices 2% per year. This regime lasted 250 months. At month 501, I instituted one of three rent decontrol regimes: (1) a "no change" regime in which rent regulations did not change; (2) a "luxury decontrol" regime in which controlled apartments whose renters had incomes greater than the mean income of those in controlled apartments were decontrolled; or (3) a "sudden decontrol" regime in which all apartments were suddenly decontrolled.

I ran ten different simulations of each of the four conditions (no controls, rent control constant, sudden decontrol, and luxury decontrol). I seeded the random number generator of each ten simulations within each condition with the same initial value to eliminate any errors that might emerge due to an outlier seed. To achieve meaningful aggregate descriptive statistics, the results for each of the ten runs were averaged. The results below are the averaged results.

RESULTS AND DISCUSSION

Like virtually all agent-based simulations, this simulation produced a wealth of data. Much more analysis could be completed. I will highlight several of the more interesting results.

RESULTS

Several interesting results emerged from the simulations presented herein. For the results described below, I did not computer any inferential statistics – instead, all results are presented descriptively only.

It is important to remember that for all the experiments, months 1 to 250 were under a regime of no rent control, months 251-500 were under a regime of rent control (the specifics were described previously) or no rent control, and months 501-750 were the experimental conditions (either a type of decontrol, continuation of rent control, or again, no rent control).

Figure 2 shows the difference between tenant income (in all apartments) under the regime of rent control and no rent control. Notice that for the first 60 months or so (251-310), there is virtually no difference between the two regimes. Yet, there is a continual divergence between the tenant income in the two regimes.

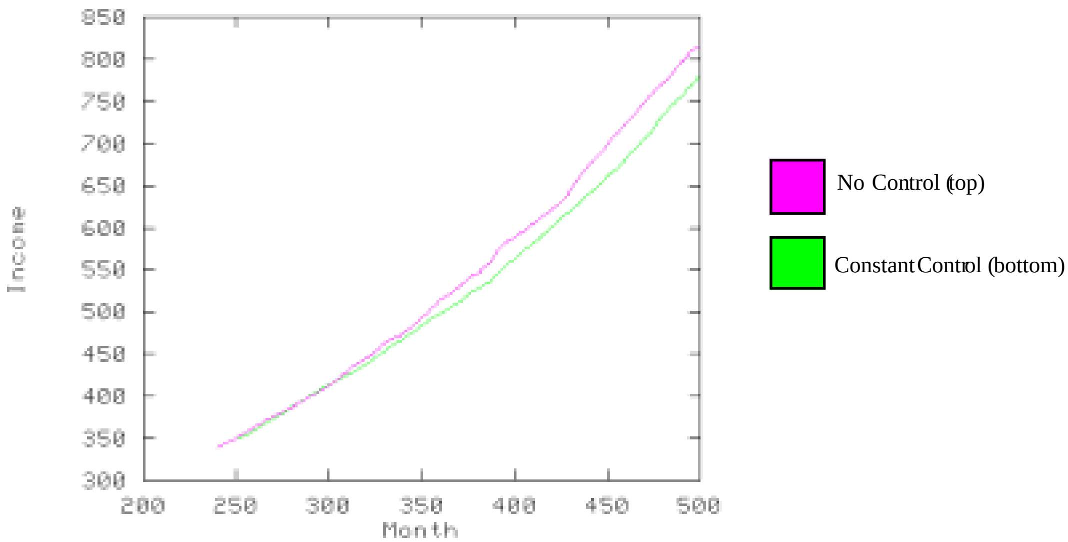

Figure 2: Tenant Income: Rent Control vs. No Rent Control

Thus, it appears as if rent control does manage to provide housing for those renters whose rental budgets (a proxy for income) are less than those who exist in the non-rent control regime. In terms of policy conclusions, the simulations suggest that rent control does provide more affordable housing for those residents that choose to live under such a regime.

Figure 3 shows tenant income during three regimes during the latter months of the simulations. It shows the difference between tenant income (in all apartments) during a market that never had rent control, a market that still has rent control, and a suddenly decontrolled market. Notice that although tenant income in the suddenly decontrolled market almost reaches to the level of the uncontrolled market, it eventually drops back down to a level similar to the continually rent controlled market.

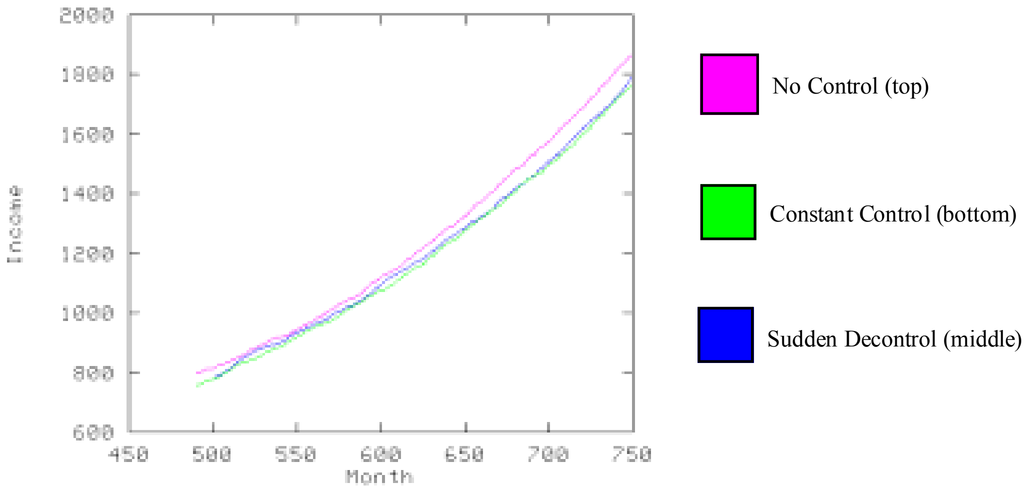

Figure 3: Tenant Income: Rent Control vs. No Control vs. Sudden Decontrol

Thus, it appears that even though at month 501 there was a return to a non-controlled housing market, in the long term, incomes in the region remained lower.

Figure 4 shows tenant income disaggregated by those living in controlled and uncontrolled apartments. Notice that tenant incomes in controlled apartments are greater than those in uncontrolled apartments. This is not as surprising at it may appear because apartments were controlled were required to have their assessed values greater than the average, and thus, people with higher budgets could afford them.

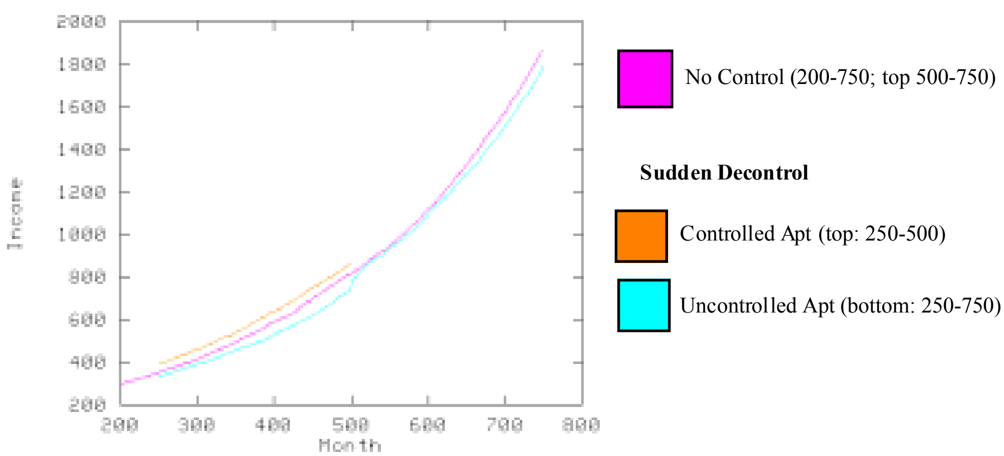

Figure 4: Tenant Income - Controlled and Uncontrolled: Sudden Decontrol and No Control

Thus, it appears that rent controls favor those with higher incomes, at least initially – of course, this pertains specifically to the method of control instituted in this example. Also, incomes of those in controlled apartments also decreased slightly in comparison with a completely free market. This suggests that rent controls benefited those in uncontrolled apartments.

Figure 5 shows the price charge by landlords during rent control and the regime of sudden decontrol. Notice that when decontrol occurs, the price dramatically jumps and then settles somewhat, before rising again.

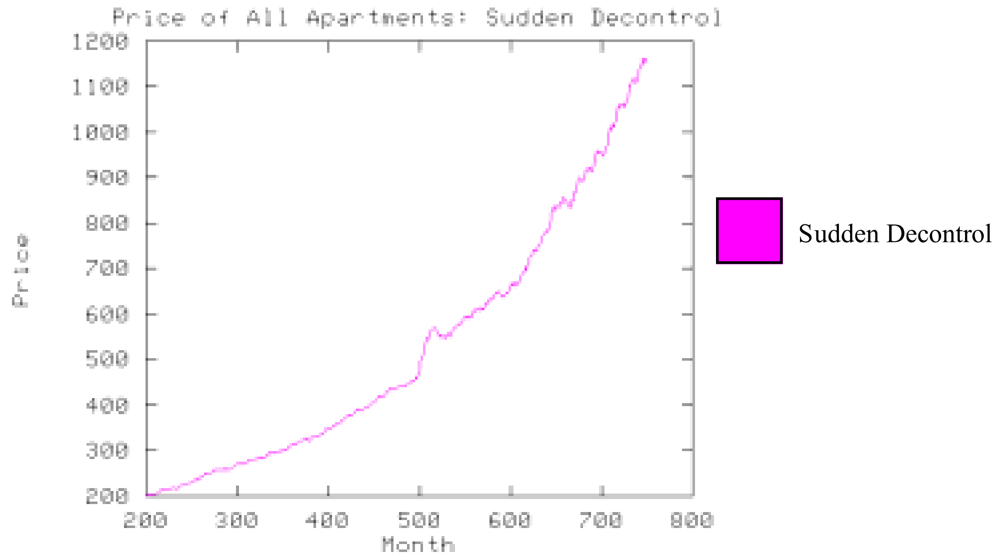

Figure 5: Price of All Apartments: Sudden Decontrol

Thus, it appears as if sudden decontrol causes prices in the market to jump.

Figure 6 shows a comparison between the price of apartments during luxury decontrol and sudden decontrol. Notice that the same rise and fall is apparent during luxury decontrol as seen in the sudden decontrol in this figure and Figure 5. Interestingly, prices in the market are virtually the same approximately four years after decontrol for the next five years, when they diverge again.

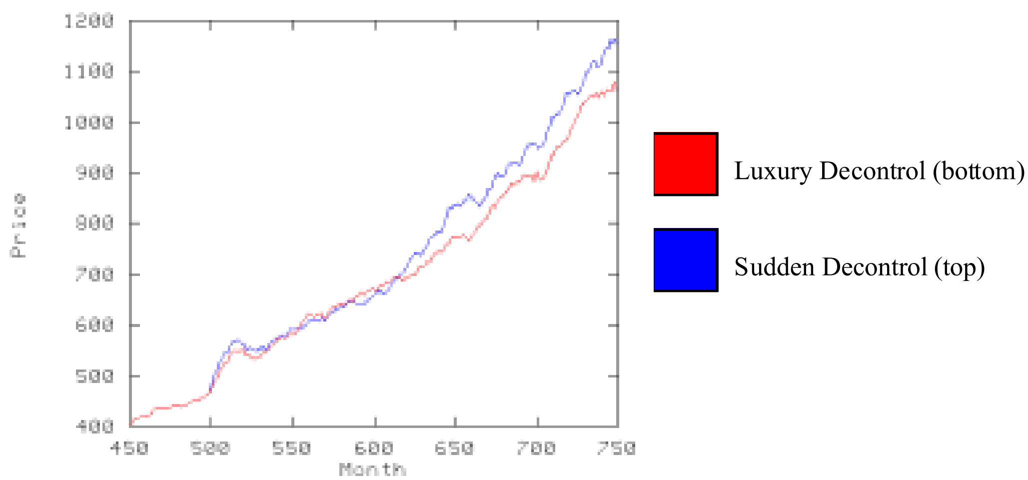

Figure 6: Price of Apartments: Sudden vs. High Income Decontrol

Thus, it appears as if in the medium term (5-10 years) simply decontrolling apartments for those with high incomes does not cause prices to be lower than if all apartments were decontrolled. Yet, in the short and long terms, the prices in the luxury-decontrolled market are less.

Figure 7 shows the quality of apartments in an uncontrolled market and a suddenly decontrolled market. Notice that overall quality of apartments is less in the controlled market initially, becomes approximately the same, and then decreases. When the market is suddenly decontrolled, however, overall quality of apartments dramatically increases.

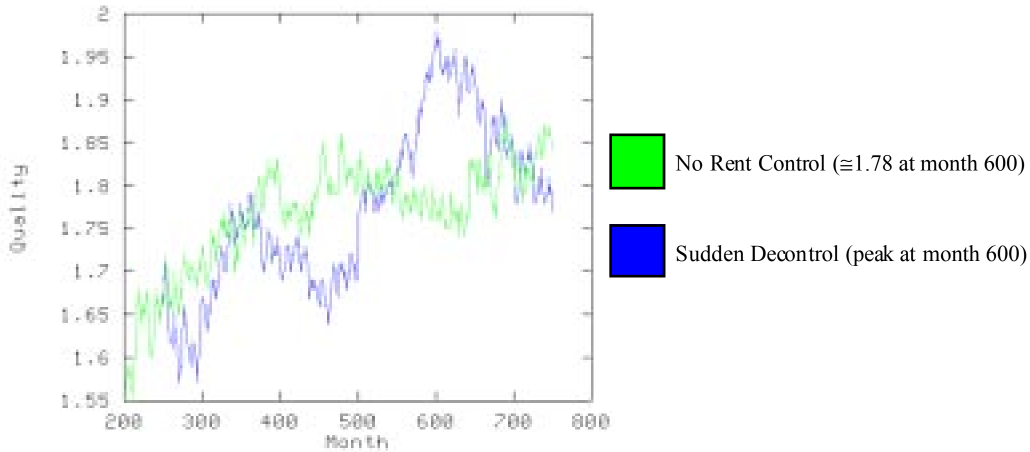

Figure 7: Quality of Apartments: Sudden Decontrol vs. No Rent Control

Thus, it does appear that, for the most part, quality of apartments is lower in controlled markets than in uncontrolled market, but not dramatically. When markets are completely decontrolled, quality increases, but eventually settles down to the uncontrolled level.

Figure 8 shows the vacancy rate of all apartments in each of the four conditions. Notice that during the period of rent control or no rent control, vacancy rates are lower in the rent controlled market. During the decontrol regimes, notice that while the constantly controlled market remains the same, the vacancy rate of the suddenly decontrolled market sharply increases, while the luxury decontrolled market's vacancy rate is similar to the uncontrolled market.

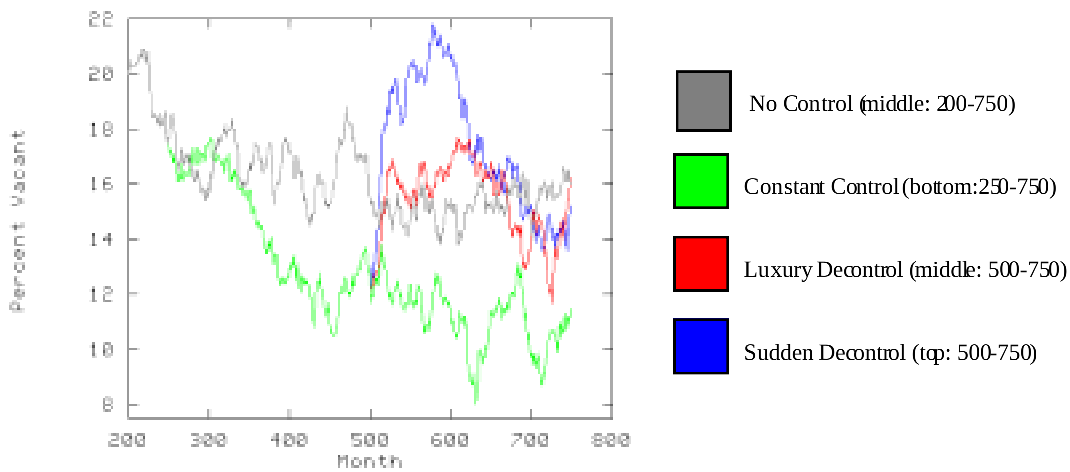

Figure 8: Vacancy Rate: All Conditions

Thus, this suggests that although the housing market is tighter during periods of a great deal of rent control (where 30% of all units are controlled during time 251-500), when rent controls are lifted from apartments being rented by wealthier renters (leaving poorer renters in controlled apartments), the vacancy rate approximates an uncontrolled market. Also, suddenly decontrolling a market can cause great upheaval in the market, apparently due to the unaffordability of the apartments.

CONCLUSIONS

I have shown how an adaptive agent-based model can represent a concrete situation in planning. I tried simulating different decontrol policies to see what effect they would have on the housing market. Certainly, more work needs to be done – including a more formal statistical analysis.

FURTHER WORK

Although this analysis suggests interesting, and somewhat unexpected, results, much more work can be completed.

First, much more work needs to be completed on systematically testing the parameters and equations of the model. Then, I can complete a formal sensitivity analysis.

Second, renters are heterogeneous in their preferences for tradeoffs involving quality, distance, and price. In this experiment, all renters were homogenous.

Third, I could rework and experiment with the adaptation formulas for the landlords – including seeing if there is an optimal strategy for pricing an apartment. Furthermore, it is important to add a representation of landlords' revenues and costs, including property taxes.

Fourth, it is relatively simple to add a larger lattice, and thus, more apartments. In addition, more apartments might be added in each cell of the lattice (thus making it three-dimensional.

Fifth, although not discussed in this paper, lease renewals achieved a measure of seasonality; that is, there were certain times of year that many apartments were on the market and other times of year when virtually none were. Such an effect was not pre-programmed into the model – it emerged from the interactions of the renters and the landlords. This effect and other intended consequences should be explored.

Sixth, more decontrol provisions, specifically vacancy decontrol, should be added.

Other suggestions are more than welcome – please write the author directly.

PRACTICAL USE OF ADAPTIVE AGENT-BASED MODELING

Some computer simulation models in social science could been thought of as distancing humans and their interactions from reality, by representing humans as homogenous groups, with perfect omniscience and economic rationality acting in a limited capacity on a limited set of options in a perfect market. Adaptive agent-based simulation models do not have to function in this manner, however; they attempt to represent the human actor in a situation directly, with limited cognition and bounded rationality (Arthur, 1994).

Even though they are complex and difficult to calibrate, adaptive agent-based simulation models have the potential to assist both academic and professional planners in their work by providing insight and starting points for meaningful discussions. Thus, using such a model in a professional office would likely require external model development and professional services to operate such a model. Nevertheless, the results that such a model produces can be used not a normative policy prescriptions, but as frameworks for informing meaningful policy discussions.

Similarly, the academic planner can benefit from such simulations. By constructing such a simulation himself or herself, or, more likely, collaborating with a colleague that may have the skill to successfully program a computer to do such a simulation, an academic planner forces himself or herself to lucidly explain the exact nature of the situation he or she is trying to explain. Such formalization of theory undoubtedly can only help all planners by making theory more explicit, and therefore less obfuscating, more easily understandable, and, in the end, more widely publicized.

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