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# An Agent-Based Model of Mortality Shocks, Intergenerational Effects, and Urban Crime

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## Abstract

Rational criminals choose crime over lawfulness because it pays better; hence poverty correlates to criminal behavior. This correlation is an insufficient historical explanation. An agent-based model of urban crime, mortality, and exogenous population shocks supplements the standard economic story, closing the gap with an empirical reality that often breaks from trend. Agent decision making within the model is built around a career maximization function, with life expectancy as the key independent variable. Rational choice takes the form of a local information heuristic, resulting in subjectively rational suboptimal decision making. The effects of population shocks are explored using the Crime and Mortality Simulation (CAMSIM), with effects demonstrated to persist across generations. Past social trauma are found to lead to higher crime rates which subsequently decline as the effect degrades, though 'aftershocks' are often experienced.

**Keywords:**
Agent-Based Model, Crime, Bounded Rationality, Life Expectancy, Rational Choice

Quaint old town of toil and traffic, quaint old town of art and song, Memories haunt thy pointed gables, like the rooks that round them Throng

from "Nuremburg," by Henry Wadsworth Longfellow

If I knew I was going to live this long, I'd have taken better care of myself.

Mickey Mantle

## Introduction

**1.1**

The struggle to understand the criminal phenomenon reaches as far back as social theory itself (Ferri 1898). There is no social science without a distinct effort to explain crime, each shining its respective analytical light on the stylized facts of incidence, magnitude, and persistence that make crime a social universal. Economists were actually quite early to the fray as Adam Smith (1981 [1776]) noted that the motivation for crime was the same as any other wealth producing activity. In modern economics the most prominent effort was put forth by Gary Becker (1968), as always applying the tools of the economist in ways not previously imagined. Becker, and others who have subsequently employed a rational choice approach to social theory (Coleman 1990), have not been without their detractors (Cook and Levi 1990), and it is with their criticisms in mind that this paper and its model are motivated.

**1.2**

The majority of the work by economists in studying criminal phenomena can be divided into three categories: rational choice modeling using comparative statics a lá Becker, multiple-regression analysis of macro variables (Trumbull 1989; Corman and Mocan 2000; Donohue III and Levitt 2000), and more recently dynamic programming and optimal control theory (Davis 1988; Leung 1995). Such analysis is no doubt valuable, but it does operate in something of a disciplinary vacuum, with subsequent work doing little to address the inherent shortcomings of the methodology. When employing regression and comparative statics techniques, the social and environmental context of agent decisions can easily become obscured, or worse, consciously ignored as sufficiently irrelevant (McCloskey 1996). This undersocialization of economic theory is at the heart of criticisms of the forays of economic theory into the traditional "turf" of other fields. Additionally there are some misleading results due to the lack of intertemporal effects, though these are largely brought to bear in the dynamic programming crime literature.

**1.3**

Efforts to model the determinants of crime rates typically begin (and often end) with poverty rates. While socioeconomic status has much explanatory power in this regard, a large literature indicates that it is not the entire story, particularly with regard to severely disadvantaged neighborhoods (Wilson 1987). The idea of "structural disadvantage" was introduced by William Wilson, and further validated by Krivo and Peterson (1996). While structural disadvantage is a broad, amorphous term, it can be said to generically refer to qualitative local cultural conditions, such as the lack of conventional role models, institutions, and social buffers. These structures bear distinct spatial and network characteristics which are extremely difficult to analyze with traditional econometrics and comparative statics (Manski 1993; Durlauf, Young et al. 2001).

**1.4**

In studying crime economists have followed a handful of avenues, taking the course of exploring crime as a rational choice made in the face of countervailing costs and benefits. Following the seminal work of Becker, significant work has been undertaken to analyze the effects of punishment and deterrence efforts (Ehrlich 1996; MacDonald 1998; Motchenkova and Kort 2006 (forthcoming)). The effects of deterrents were explicitly explored for urban areas by Vijay Mathur (1978). The epidemiological approach taken by Philipson and Posner (1996) in their effort to explore crime and the response of citizenry is of relevance as a natural rate of crime is demonstrated to emerge from indirect interactions of criminals and legitimate citizens.

**1.5**

Sociologists of the ecological school have followed in the footsteps of the work of Shaw and McKay whose research on urban delinquency (1942) explored the environment as a source of causal factors of crime. Environmental criminology (Bottoms 1997) emerged as an effort to map crime to a model of urbanization, sparked by the Mayhew's *London Labour and the London Poor*, and then pushed to the forefront by the work of Shaw and McKay. These efforts led to a rise in research in crime and causality by urban geographers (Herbert 1982). In particular, the work of Harries (1973; 1980) demonstrated the strong regional characterization of crime on both the state and intra-urban level.

**1.6**

The bulk of the work reviewed was constituted by positivist, empirical work, and for that it is to be admired; the data is difficult and expensive to collect, to say nothing of the challenges of interpretation and analysis. That said the nature of crime and causality is fraught with analytical peril: the data generating mechanisms and underlying distributions are always in the question, the value of "statistical significance" is dubious, and the historical propulsion and propagation of trends is largely beyond their scope. Glaeser et al (1996) build from the empirical data a notably socialized model and in the process get at the nature of the underlying distributions and the variance of crime data across time[1]. It is with similarly inspired motivations that in the following sections we will build a model of urban crime that demonstrates the potential to extend and build upon this research using agent-based simulations as a modeling methodology.

**1.7**

The underlying goals of this modeling effort are, first, to demonstrate the potential for agent-based representations of rational choice models of crime and other empirically observable urban phenomena, and second, to offer and test a specific hypothesis relating past mortality shocks to regional crime levels several generations later, in particular when those regional levels reflect a significant break from trend. While crime is without argument an ubiquitous phenomenon, it has a greater association with the city than the countryside (Glaeser and Sacerdote 1999), and as such has received significant attention from those pursuing urban studies. The topology of the agent-based model is a natural analogy to the urban landscape, with its explicit locational contexts and relationships. As such, an agent-based model of crime is a natural fit for urban settings. This interactive topology, along with greater heterogeneity of agents, while retaining the temporal nature demonstrated important by dynamic programming models, allows for agent based models to offer a rich explanation of criminal phenomena. Further, the creation of artificial timelines of data allows for the examination of underlying distributions, and evaluation of hypotheses regarding historical impulse and propagation of trends.

## Foundations of the Model

2.1

Much of social phenomena has so baffled academics that Talcott Parsons long ago pronounced economics to be the study of the rational and sociology the study of the irrational (Parsons 1949). Fears of hubris aside, the interdisciplinary field of sociology and economics (Swedberg 1990) has made great strides in demonstrating that the individuals that inhabit the sociologist's world need not be irrational to explain how seemingly sub-optimal phenomena can emerge. This work has been largely limited, however, by the neoclassical framework, with its representative agents, non-spatial landscapes, infinite connectivity and time-absent instantaneous emergence (Potts 2000).

2.2

Agent-based modeling has a tremendous upside to offer economic studies of social outcomes and historical trends specifically because it allows the researcher to actually generate, or grow, the outcome in question in a stylized world whose base framework more closely resembles the one in the which the history actually took place (Epstein, Axtell et al. 1996). These strengths are only reinforced when applied to the sociology and geography of urban landscapes, where a large number of agents can be realistically modeled as living in close proximity to one another, with clearly defined locational contexts and regional demarcations. The fact that we identify "urban settings" as an environmental classification worthy of specific sociological investigation only reinforces the notion that spatial proximity and physicality matter.

2.3

It is with this diverse family of research in mind that the Crime and Mortality Simulation (CAMSIM) is designed[2]. The methodological goal is simply stated, but considerably more difficult in execution: to have a rational agent, making economic choices, operating with reasonable cognitive and informational limitations, and all the while living within the context of time, location, and a socialized community of heterogeneous agents. The model created is founded on theory from several fields, while hopefully internalizing their criticisms of one another as well.

### Rationality

2.4

The nature of rationality within any model is a major source of contention, as different fields are generally associated with specific models of decision-making. CAMSIM is first and foremost designed as a rational choice social model, and as such does not portend to offer answers in the debate specifically regarding rational choice. Within the world of rational choice, however, it should be considered a model of bounded rationality, with more than a bow to Herbert Simon (1959; 1982; 1986). Simon suggested that rationality might be more realistically modeled by either limiting computational accuracy or functional form, using vector rewards in utility formation, or, as in the form reflected in CAMSIM, by recognizing the economizing on information that agents must often resort to. As will be explained in greater detail later in the paper, agents employ a decision heuristic dependent on local information, rather than, say, employ fuzzy computations or add an error term. This local bounding of information can be interpreted as a simulation modeling of the "availability heuristic,"(Tversky and Kahneman 1974). Agents place a disproportionate weight on sample information made immediately available to them, assuming that it is representative of the greater information population. As such, there can evolve for each individual a subjective reality[3] based on a local set of information quite distinct from the global reality they are making decisions within (Simon 1955). This is analogous to the delineation within the crime literature between objective and perceptual crime patterns (Brantingham and Brantingham 1981; Brantingham, Brantingham et al. 1986; Harries 1988). With regards to agent behavior there is within economics the concept of local versus global maximization. The public goods dilemma is often couched in these terms as agents, engaged in a never-ending prisoner's dilemma with their fellow agents, consistently maximize locally, forever preventing the greater good of the globally maximized state. Analogously, agents in CAMSIM are maximizing in accordance with local information regarding their time horizon, while failing to maximize relative to the underlying probabilities governing their world.[4]

### Human Capital

2.5

The bulk of the work to date by economists in analyzing crime has focused on the effects of deterrence efforts (incarceration probability and duration, capital punishment, etc...) and the costs with regards to macro efficiency and production. The analysis here, rather, is concerned with the decision to pursue a "criminal" career. As such the microeconomics of career choice represents the relevant literature, specifically the efforts by Behrman et al. (1998) to cast choices related to college and career as questions of human capital investments and payoffs, an effort reinforced by Keane and Wolpin (1997), both of which represent work built on Becker's theory of human capital regarding education (Becker 1964).

2.6

CAMSIM, however, makes no attempt to model decisions of how much to invest in career related human capital, but rather whether to invest at all. Career choice is reduced to three broad fields: professional (requiring an education investment), labor (no investment), or crime (negative investment). By modeling the career as a one-time, irreversible decision, the time horizon is critical to the utility-maximizing agent (Hamermesh 1985). As such, subjective life expectancy is the agent's time horizon, and thus is the critical independent variable fully endogenized in the utility function governing agents in CAMSIM. This inclusion of life expectancy in career-related decision making was explored by Teahan and Kastenbaum in a small empirical study seeking to link SLE with job-success (Teahan and Kastenbaum 1970). Within their sample the authors find that

> Major consistent differences in subjective life expectancy...were found between successful and unsuccessful employees...Employees who failed to stay on the job were found to have shorter lifespan predictions.

In short, those with longer SLE's were more interested in building human capital in the form of occupational experience and tenure. The notion of an agent's time horizon as related to his propensity, or potential, to commit crime was explored by Banfield (1970), casting the criminal as being more "present oriented" - essentially agents with higher discount rates of time are more likely to weigh the benefits of crime higher than the costs. Discounting and temporal factors are explored in much greater detail by Wilson and Herrnstein (1985), noting that crime, versus non-crime, is differentiated by benefits preceding costs. Wilson presents this differentiation as a set of benefit and cost curves based on the laboratory studies of Farrington and Knight (1979). It is with these results in mind that the model is initially parameterized.

2.7

It is important to note that agents in CAMSIM have uniform time preferences in the form of discount rates. Internal discount rates are inherent to the individual; agents with higher discount rates are *ex ante* predisposed towards crime[5]. CAMSIM is homogeneous across the agent population with regards to instantiated predisposition towards crime, testing instead the effects of heterogeneous information, based on the rationale that information sets can change much faster than the inherent characteristics of the agents themselves.

### Life Expectancy

2.8

Time horizon is factored into the CAMSIM model as the life expectancy of the agent. Part of what distinguishes the CAMSIM model is the uncertainty and imperfect information that agents face in forming their time horizon, specifically their subjective life expectancy (SLE). Denes-Raj and Ehrlichman (1991), Hamermesh (1985), and Nelson and Honnold (1980) all report empirical evidence that strongly support the hypothesis that individuals disproportionately weight the early death of near relatives in the formation of SLE. Such work underpins the modeling of the SLE formation as an explicit socialization process (Nam and Harrington 1986). In moving from the empirical to the artificial, we extend the definition of socialization, positing that we can model socialization as the process of emergence of patterned social phenomena and historical trends from the stochastic interactions of heterogeneous agents.

### Objectives of Modeling

2.9
There are many goals for a social simulation, but for the most part they can be broken down into two broad categories: validation and calibration[6]. Validation is the demonstration that a social phenomena can be grown in a model that operates on simple, realistic assumptions that sufficiently mirror the world being abstracted from. The parameters employed in such a model are important, but nonetheless arbitrary in their assignment, with the understanding that is only their signs and relative magnitudes that are informative. Calibration, on the other hand, is the specific tuning of the model and its parameters to historical, empirical evidence in an effort to understand the specifics of the phenomena in question with significantly increased resolution. The model presented here is one of validation, though empirical and experimental data is employed to justify the decision functions, parameter values, and information limitations key to the results that emerge[7].

## CAMSIM

3.1
As has been pointed out by McCloskey (1998), even the most austere mathematical model is still just a story. CAMSIM is no different in this regard, and it is one of the great strengths of agent-based methods that they can be translated into stories almost effortlessly. CAMSIM agents live on a two-dimensional lattice not unlike a checkerboard, with the environment divided into "patches." An agent is born and lies underneath her parent (CAMSIM agents are asexual) agent until age 16, at which time she chooses a career and moves to her own patch. This career choice is the heart of model, and reflects a simple maximization based on life expectancy. The agent will move upon maturity and location selection is purposely designed such that the agent will always choose a patch in her original neighborhood if available, only moving beyond in the face of a maximally occupied locality. As such the life spans of past relatives are disproportionately represented; the socialization process is dominated by, but not limited to, family. Not to be ignored is the simple reality constructed: time passes; agents age, reproduce, and die. An agent's chances of dying each turn depend on her career and how old she is[8]. Agents reproduce asexually, producing a set number of births per 1000 agents each turn. An agent may only reproduce between the age of 16 and 45.

3.2
In simple economic terms, career selection is represented by agents choosing a parameter set for a production function of utility that maximizes their lifetime utility over the time horizon they anticipate. In this context, time represents a resource whose relative scarcity or abundance is estimated by the agent. Rationality is thus bounded as agents employ a simple heuristic, with limited information, in choosing which parameter set (career) maximizes their lifetime utility production.

3.3
The objective function in question, Lifetime Utility ($U_i$), is calculated for agent *i* using Formula 1:

$$\max U_i : U_i = a + \frac{b(1 - e^{-r(\mathrm{E}(\mathrm{L}_i) - c)})}{e^r - 1} \tag{1}$$

where *a* is the lump sum payment received for choosing the occupation, *b* is the income received each turn in the simulation, and *c* is the turns spent pre-employment.[9] Agents discount future utility at a uniform interest rate, *r,* of 3%. The heuristic for SLE, Expected Lifespan, $E(L_i)$ [Formula 2] is a function of the average lifespan, $\hat{L}$ , of each patch, *j*, in the agents neighborhood of $n_i$ total patches.

$$E(L_i) = \sum_j \hat{L}_j \Big/ n_i \tag{2}$$

The lump sum *a* is positive for the criminal (pecuniary and non-pecuniary benefits inclusive), zero for the laborer, and negative for the professional (education costs). These parameters are in alignment with the experimental findings of Farrington and subsequent analysis of Wilson. Income is an adjustable parameter for each occupation, but for simulations pursued here it is assumed that laborers earn a yearly income greater than criminals, and professionals in turn earn an income greater than laborers. In such a model what matters is not absolute lifespan, but rather lifespan relative to the lump sum benefits of crime, the costs of education, and the lifetime earnings potential of skilled and unskilled occupations. In such a world crime can persist in the face of a growing economy, so long as the *a*'s keep pace with the *b*'s.

3.4
As the model progresses a small portion of the adult population will move every turn, reflecting a certain amount of population mobility. More importantly, a portion of the population will die every turn. Whether or not an agent dies each turn is based on a set of probabilities built into the model that are set by the user. It is important to note that agents are completely ignorant of these probabilities. Decision making is based on local mortality history, and as such they may make decisions that while subjectively rational, can in fact be objectively irrational. This would appear to get at the question that, at the deepest levels, motivates so much scholarly interest in the psychology of the criminal, specifically, why would someone rational choose a criminal path when a more rewarding life is possible in alternative, socially accepted means? Questions of aptitude and comparative advantage aside, there are no doubt many individuals committing crimes every day that could live longer and receive greater financial rewards from socially legitimized occupations.

3.5
The character of any economic model is shaped by its assumptions, and this model is no different. An observer, especially one mindful of the limitations placed on individual agents, will be quick to note that agents in the cityscape treat life expectancy as exogenously determined[10]. This is of course a profound simplification of human beings and how they form their expectations, but in trying to build a model where within agent decisions are shaped by their environment (Simon 1956), it is not beyond reason. Work already cited points towards the over weighting of relatives' lifespan in forming subjective lifespan expectations. Further, the death of a parent has been shown to have a tremendous negative impact on expectation formation. Beyond just parental relations, however, there exists the more complex character of environmental psychology (Fisher, Bell et al. 1984), where the subjective life expectancy of the individual is no doubt affected by the region he calls home. Can there be little doubt that an inner city youth experiences more hazardous formative years than his suburban counterpart (Taylor 2001)? An indirect, but related example can be found in the profound drop in the crime rate of New York City that is connected by many to the cleaning of graffiti from subways (Gladwell 2000), something which is often cited as a prime example of the "broken windows" theory (Wilson and Kelling 1982; Kelling and National Institute of Justice (U.S.) 1999) of urban crime in effect. If such a change in environment were to lower the subjectively determined expected probability of being the victim of crime, it would increase subjective life expectancy, and in turn, within a model such as CAMSIM reduce the crime rate, creating a positive feedback loop. Conversely, a negative shock to the information environment could create a negative feedback loop.

## Exploration

4.1
The model in question can be explored in countless ways, but for this paper we will be focusing on the effect of extended population shocks. The method employed is directly akin to those used in Monte Carlo simulations. The model was initialized with a specific set of parameters and run 100 separate times, with 200 turns (or years, if you will) constituting a run. The initialization of a run is (pseudo) random, as are all of the stochastic elements of the model.

4.2
The environment used in the experiment took the form of a 39 by 39 grid, divided into 4 separate regions, allowing for 1444 total available patches[11], with each region a 361 patch grid. The initialized population inhabited 70% of the space, with a total of 1064 agents, with a mean age of 55. The model was initialized with 95% of agents over the age of 15 given the "labor" occupation, while the remaining 5% of adult agents given the "criminal" occupation. 2% of the population was randomly selected to move each turn. The underlying, objective reality of the model regarding mortality is set with professionals bearing a 1.0% chance of dying each turn, laborers 1.3%, and criminals 3.0%. The adult population was assigned a reproduction rate of 55 births per 1000 agents every turn.

4.3
The key to the experiment in question was the exogenous shock distributed to one of the regions in each simulation run. At turn 40, the northwest quadrant (Region 1) was hit with a mortality shock[12] that resulted in the death of approximately 5% (15 agents) of its region's population. This shock then recurred

each turn for 10 turns (40 - 49). "Shock" deaths were in addition to any deaths which occurred as result of the standard probabilistic algorithms. For comparison, a control experiment with identical parameters, but without the mortality shock, was conducted. The crime rate steadily increases at first, and then begins to fall as the pool of available information increases. The experiment conducted is a shock to this pool of information; it is expected that crime rates in the shocked region will exceed that of the non-shocked region, and that of the control experiment, for a considerable period of time following the shock, as the traumatization of the local information set accessed by agents will exist as a legacy in the socialization process.

### Results

4.4

The experiment generated one hundred sets of time-series data. This data is explored on a number of levels, but what we are most interested are the 1) Comparisons of total criminals and criminal percent of population between the shocked and non-shocked regions, and 2) Comparisons of the different simulation runs, specifically the distribution of criminal measures at each turn of the experiments (i.e. the mean or variance of criminal percent at turn 37 across the simulation data).

#### The Children of Disaster

4.5

The mean criminal percentage (Figure 2a) is significantly higher in the shocked region, and persists for the full 150 turns after the shock. During the shock the rate of growth in the crime rate accelerates; this is a result of the 2% of agents that are mobile between regions every turn. The crime rate lowers after the shock passes and begins to level off, though at a rate higher than the other regions. Time passes and then an "aftershock" of crime emerges, as the generation of parents and grandparents who chose criminal careers fall victim to the higher probability of death of their respective career, which bears a disproportionate effect on their offspring which have remained in neighboring patches. The lower mean percentage in the shocked region during the shock is a result of the strong, albeit temporary, shift in the age profile of the region; random deaths do not discriminate by age and as such fewer agents during the shock progress to the stage of choosing a career.

#### The Grandfather Effect

4.6

There are often observable "bumps" in the shocked region, fifty to one hundred turns after the shock. Examples can be found in Figure 1, the charted percentage of each region's population that has chosen the "criminal" occupation in the first four of 100 simulation runs. While we cannot directly infer anything substantial from any one simulation run, it serves as a representative case[13].These bumps are smoothed away in the mean, but are represented in the radical divergence in the variance of crime [Figure 3] in the shocked region compared to the relatively low and stable variance of the non-shocked regions. Here we find criminals whose decisions are indirectly influenced by events long since past, and a turbulence in the crime rate across time in any one realization that resonates with the Glaeser et al(1996) work identifying social interactions as playing a major role in variance in crime rates over time.

#### Diffusion of Criminals

4.7

As expected the crime rate explodes during the shock: the perceived life span plummets and children choose to be criminals at a greatly heightened rate. The effect is strong enough that it bleeds over, somewhat, to the other three regions. The source of this diffusion is largely the baseline adult mobility in the model (2% of the adult population moves every turn), but additionally maturing agents in saturated neighborhoods may move to other regions as well.[14] This process of diffusion is evident in the change in slope in figure 2a at time 50, as the rate of growth in the criminal percentage accelerates, taking it well beyond the peak in the control experiment charted in figure 2b. Once the shock ends the crime rate begins to slowly drop in the shocked region, while the non-shocked regions return to previous levels significantly faster.

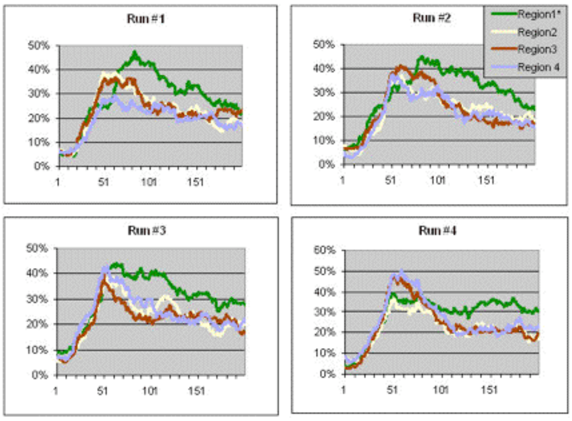


**Figure 1**. Runs #1, 2, 3, and 4 of 100. Each compares all four regions. Region #1 experience a morbidity shock in from time 40 until time 49. Regions 2 - 4 were not shocked, but 2% of the adult population moves each turn

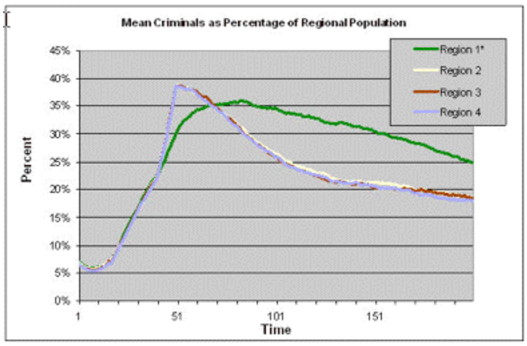


**Figure 2a**. The mean percentage of each region with a criminal career, across 100 runs, each consisting of 200 turns, with a 10 turn mortality shock in region 1 at turn 40

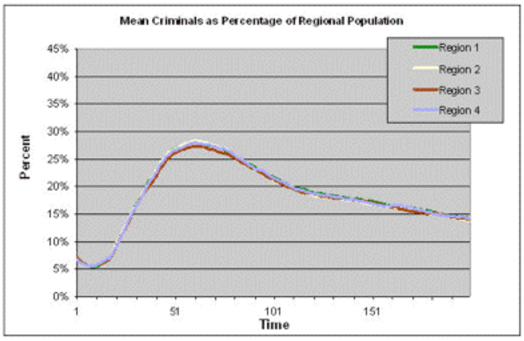


**Figure 2b**. Control Experiment; The mean percentage of each region with a criminal career, across 100 runs, each consisting of 200 turns, without the mortality shock. Note that the peak (~ 28%) is considerably lower than in 2a, as is the final rate (~ 14%) The rate of crime rises early while information is limited, but drops naturally as the history develops and agent information sets come to reflect the underlying probabilities governing the model

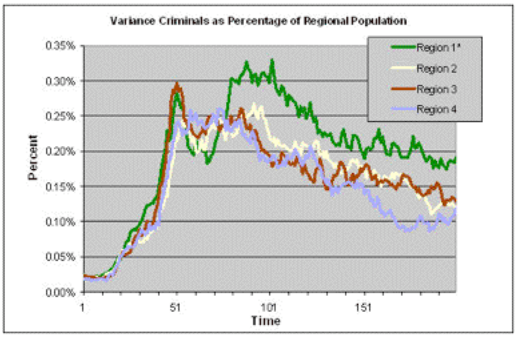


**Figure 3**. The variance of the percentage of each region with a criminal career, across 100 runs, each consisting of 200 turns, with a 10 turn mortality strike at turn 40

### Connection to Relevant Data

**4.8**

William Wilson referred to the severely disadvantaged as "structurally disadvantaged." There exists in the data a significant discontinuity in the relationship between crime and poverty. The work by Krivo and Peterson (1996) revealed a significant jump from trend in the rate of violent crime within severely disadvantaged communities. The imprint of traumatized information sets on the expectations of young community members could be interpreted as exactly this kind of structural disadvantage. Local shocks to information, from epidemics, riots, or other tragedies can be connected to future increases in crime, as well as to the economic and crime discrepancies between otherwise similar regions and neighborhoods.

**4.9**

The simulation data created is difficult to compare to historical record, being relevant to large swaths of history, and U.S. data of record only going back to just after World War II. The data, as charted in Figure 4, does demonstrate a strong spike in the crime in the generation after WWII, an eventual decline, and an increased bumpiness whose spikes could be interpreted as aftershocks. While this is not enough to validate the model, its shape certainly would appear to credit it as warranting further investigation. Future calibration of the model would require not only a temporally larger data set, but also multiple nations or regions. The most likely candidate for validation of the model and verification of parameters would appear to be comparative lets of county or municipal data, particularly those with significant historical shocks to local mortality rates.

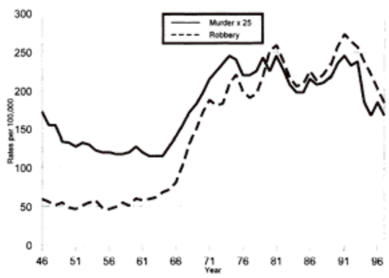


**Figure 4**. from Lafree (1999), Murder and Robbery Rates, 1946 -1997, data supplied by the U.S. Federal Bureau of Investigation, "Crime in the United States," Uniform Crime Reports annual, 1946 to 1997 (Washington D.C., Government Printing Office)

### Feasibility of Bounded Rationality

**4.10**

An additional control experiment was run to demonstrate that left to themselves the admittedly myopic agents constructed in CAMSIM will uncover a subjective determination of lifespan that closely approximates what one could mathematically determine with the underlying probabilities, if they were known to them. Table 1 represents the data from 100 control runs of the model, each lasting 250 turns, where Mean Differential indicates, averaged across the 100 runs, the difference between the mean subjective life expectation of the population and the mean life span at that time. As expected the differential decreases as time progresses, but perhaps just as importantly, the differential is relatively small after only a small number of turns. Further, the natural tendency of the model is demonstrated to be a bias towards *overestimating* expected life, and away from criminal career choice.

**Table 1:** Rationality Control Experiment

| Turns Completed | 50 | 100 | 150 | 200 | 250 |
|---|---|---|---|---|---|
| Mean Differential (SLE - Mean Lifespan ) | -1.73 | 3.61 | 3.83 | 3.08 | 2.59 |
| Percent Differential (Differential / Mean Lifespan) | -3.64% | 7.24% | 7.52% | 5.95% | 4.96% |

## Conclusions

**5.1**

In a model such as CAMSIM a historical anomaly can act as the seed for future behavior that is, from standard methods of analysis, ostensibly irrational. A mortality shock can act as an impulse mechanism, causing the crime rate to break from trend. From there, the shocked information set, and the greater preference for high-risk, quick payoff activities act as the propagation mechanism for higher crime rates. Future efforts to extend and validate the CAMSIM model, and calibrate it to reality would have to include explicit comparisons to empirical histories, in particular criminal data after wars and other disasters. An ad hoc comparison to Lafree's (1999) analysis of the post-war violent crime boom (1961-1974) and subsequent decline in the 1990's, lends at least some validation to the CAMSIM model. More significant is Lafree's conclusion that understanding crime waves requires a more historicist, time-centric approach, as well as a greater appreciation for the connection between individual decision making and broader social trends notably observed by Schelling (1978) in work widely considered the precursor to agent-based modeling.

**5.2**

Employing agents operating with locally and temporally bounded rationality allows for the modeling of sub-optimal phenomena emergent from behavior that retains its rational character. This is especially true when a phenomenon emerges as a break from trend, such as a significant boom in crime in the midst of a greater historical decline. As such it is not necessary to imply that regions of relatively high crime rates are composed of individuals whose comparative advantage lie in illicit activity[15]. Further still, it is possible that low rates of investment in human capital (education) are, again, not resultant of comparative advantages that lie in unskilled work, but rather the effect of a lowered time horizon based on local history. It does not take a major leap to juxtapose this sort of effect to non-physical localities of information, the most obvious leap being to the possibility of combining neighborhood and racial history when forming subjective lifespan expectations.

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## Notes

1 The model in their paper deserves accord for a number of reasons. Beyond simply taking the step of modeling crime as being dependent on socially interacting agents, they also employ agents that are heterogeneous in a meaningful way.

2 CAMSIM is designed within the NetLogo application (Wilensky 1999)

3 Simon refers to this as "'intendedly' rational"

4 In making an explicit effort to bound the rationality of agents there remains the valid critique that CAMSIM may be leaving behind agents of perfect omniscience only to employ agents of staggering myopia. This paper contends that 1) The other end of the spectrum must be visited before the truth can be found in the middle, 2) A rational agent of relative myopia bears a closer resemblance to reality than *homo economicus* and 3) The limitations placed upon agents in forming subjective determinations of life expectancy have been validated by empirical work to be discussed later in the paper.

5 Heterogeneity of agent discount rates could result in "genetic" drift leading directly to regional differences in crime rate, as well as various evolutionary selection possibilities. Uniform discount rates control for this.

6 This is sometimes synonymously referred to as "verification," but programmers will also use verification to refer to confirming that the program code is executing as intended.

7 Succinctly put, calibration requires the correct objective/utility function, whereas validation only requires that the form of the function is appropriate and relevant.

8 If an agent reaches age 89 he will automatically perish upon the subsequent turn.

9 This will be familiar to many as the formula for the present value of an annuity. Utility is calculated subtracting years already lived, sixteen, from the expected total. An additional 2 years are subtracted from laborers to account for finishing secondary school and, and an additional 6 years are subtracted from professionals to account for finishing high school and a college degree.

10 Less shocking, but no less important is the assumption that agent choices regarding career are irreversible. The model becomes unwieldy if agents are allowed to re-optimize later in their life.

11 One row and one column of patches were used as regional "border" patches

12 This is a generic shock; it can be interpreted as representative of a number of potential "shocks" to an urban area, such as drug-related violence, war and accompanying conscription, or an environmental health crisis.

13 Observing representative runs in conjunction with variance and spread can be useful. The real world is always "one run" as alternate realities are not typically readily available for analysis. The data must be confirmed as non-anomalous in general structure, but means and medians can "smooth away" useful information regarding how the artificial history plays out.

14 This is unlikely in this case, as the shocked region has considerably reduced population density.

15 It has always been very difficult for proponents of genetic and aptitude theories of criminal propensity to explain significant booms or busts as gene pools are not so easily shifted.

## Appendix A: CAMSIM and the Theory of Reference Groups

**A.1**

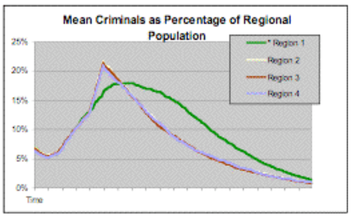
The model used in the main body of this paper does not directly include the choices made by an agent's peers in his information set. While the choices of one's ancestors are reflected in the respective life spans, the careers of neighboring agents do not enter the expected utility function. The social theory of "reference groups," a term first used by Herbert Hyman (1942), contends that an individual's consideration of her own position and options is in part a function of the persons she compares herself with as a reference group (Hyman and Singer 1968). In short, a reference group can be used as a heuristic for one's assessment of the self in making decisions.

**A.2**

CAMSIM has built into it an option by which the user can attach weights to the dominance and absence of the various careers in the reference group of the agent.

$$U_{weighted} = U^{\Phi} \qquad \Phi \in [\alpha, 1, \lambda] \tag{3}$$

Here the weighted utility, $U_{weighted}$, is a function of Utility and the reference group weighting. When an agent chooses a career (professional, laborer, or criminal) she weights the expected utility of each career: $\alpha$ if the none of the agents in her neighborhood have that career, 1 if at least one neighborhood agent has it, and $\lambda$ if it is the most popular career in the neighborhood. When the experiments from this paper were duplicated using the reference group weightings, with $\alpha$ = 0.98 and $\lambda$ = 1.02, the results were similar in character to the previous results, though the magnitudes of all of the criminal percentages were reduced proportionately.



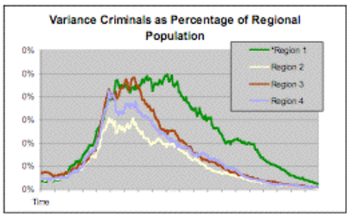




**Figure A1 and A2**. The mean (A1) and variance (A2) of the criminal percentage of the population over 200 turns, with a shock at turn 50, using the reference group weightings, α = 0.98 and λ = 1.02

## Appendix B: The model

**B.1**

An applet of the model and a link to the complete CAMSIM Netlogo source code is available online at: http://mason.gmu.edu/~mmakowsk/UrbanModel.html

**CAMSIM High Level Pseudo-code Summary**

```
(1) Main loop

While time < 201
        For each patch [p] p.calculateAverageLifespan
        Random (0.02 * total population) agents move to a new location
        For each agent [a] {
If  16 < age < 45 and (random number from 1 to 1000) < birthrate) [add new agent ]
Agents-grow-up
}

Stats-collector
        If 39 < time < 50 [random 15 of region-one agents die]
End-while

(2) Agents-grow-up procedure

For each agent[a]
        If  a = child [
                Age++
                If (random number from 1 to 1000) < childDeathRate [agent dies]
                If age = 16 [
ExpectedLife = mean [AverageLifespan from patches in Moore Neighborhood]
Calculate-Expected-Utilities
choose career with maximum Expected Utility
if local patch open [move to local patch]
                        else [if random patch open [move to random patch]]

        ]

If  a = adult [
        Age++
        If age < 50
[If (random number from 1 to 1000) < a.career.adultDeathRate [a.dies]]
        If 50 <= age < 90
[If (random number from 1 to 1000) < a.career.adultDeathRate + 20 [a.dies]
        If age >=90 [a.dies]

]

(3) Calculate-Expected-Utilities [note: the jail function has been turned off in CAMSIM for this experiment, so the expected jail time is ze

a.ExpUtilityProfessional =  ((-4 * EducationCost) + ((ProIncome * (1 - exp(- rate * (ExpectedLife - 22 )))) / (exp(rate) - 1)))

a.ExpUtilityLabor = ((LaborIncome * (1 - exp(- rate * (ExpectedLife - 18 )))) / (exp(rate) - 1))

a.ExpUtilityCriminal =  (CrimeLumpSum + ((CrimeIncome * (1 - exp(- rate * (ExpectedLife - 16 - ExpectedJail )))) / (exp(rate) - 1)))
```

---

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