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

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Abstract

This paper presents an agent-based model of urban crime, mortality, and exogenous population shocks. Agent decision making 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. The potential for social simulation as a tool for the integration of theory across multiple disciplines is explored. CAMSIM is available via the web for future research by modelers and other social scientists.

"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

1 Introduction

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.

The majority of the work by economists in studying criminal phenomena can be divided into two categories: rational choice modeling using comparative statics a lá Becker and multiple-regression analysis of macro variables (Trumbull 1989; Corman and Mocan 2000). 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.

Within the greater field of criminology the socialization of agents is not just a key part of the model, it often *is* the model. Such theory is not easily married to economic and rational choice analysis. There are, however, schools of research and thought whose paradigms more elegantly align with the economic approach. The model to be constructed and explored here is built on the empirical foundations of the ecological school of Shaw and McKay,[1] and the work generally referred to as (urban) criminal geography. This literature will be more closely reviewed later in the paper.

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 a 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.

1.1 Literature Review

Economists in studying crime 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). 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 the 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.

Sociologists of the ecological school have followed in the footsteps of the work of Shaw and McKay whose research on urban delinquency (Shaw and McKay 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 set ablaze 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.

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. 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.

2 Foundations of the Model

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 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).

Agent-based modeling has a tremendous upside to offer the economic studies of social outcomes and

[1] Often referred to as the Chicago school of sociology

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 a special environmental classification worth specific sociological investigation only reinforces the notion that spatial proximity and physicality matter.

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 computational limitations, and all the while living within the context of time, location, and a socialized community of heterogeneous agents. Such a model would not only have the potential to employ theory from several fields, but to acknowledge their criticisms of one another as well.

2.1 Rationality

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). 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," (Kahneman, Slovic et al. 1982). 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). 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]

2.2 Human Capital

The bulk of the 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

[2] CAMSIM is designed within the *NetLogo* application, Wilensky, U. (1999). NetLogo, Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

[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 bares a resemblance closer 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.

represent work built on Becker's theory of human capital regarding education (Becker 1964)[5].

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 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 (Farrington and Knight 1979). It is with these results in mind that the model is initially parameterized.

2.3 Life Expectancy

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, H. 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.

2.4 Objectives of Modeling

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

5 The Keane and Wolpin paper is interesting in that in creates an explicit dynamic model of career choice. One key conclusion was that a tuition waver would have little impact on individuals whose comparative advantage was in blue collar work. It would be interesting to see the model run with agents using bounded rationality/limited information, and then to identify the impact of a tuition waver.

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.

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].

3 CAMSIM

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 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. 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].

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.

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

$$(1)\quad \max U_i : U_i = a + \frac{b(1-e^{-r(\mathrm{E}(\mathrm{L_i})-y)})}{e^r - 1}$$

where a is the lump sum payment received for choosing the occupation, b is the income received each turn in the simulation, and y is the turns spent pre-employment.[9] Agents discount future utility at a uniform interest rate, r, of 3%.

The heuristic for 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 total patches.

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

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)[10]. These parameters are in direct alignment with

[7] Succinctly put, calibration requires the *correct* objective/utility function, whereas validation only requires that the form of the function is appropriate and creates something relevant.
[8] If an agent reaches age 89 he will automatically perish upon the subsequent turn.
[9] 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] This is equivalent to a positive *investment* (cost) for professionals and a negative *investment (benefit)* for

the experimental findings of Farrington and subsequent analysis of Wilson. Income is an adjustable parameter for each occupation, but for simulations pursued here is always 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.

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.

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[11]. 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 Malcolm Gladwell (2000) connects to the cleaning of graffiti from subways, 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 subjective 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.

4 Exploration

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.

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, 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. All agents initialized into the model over the age of 15 were given the "labor" occupation by default. All of the standard agent rules were employed. The objective reality of the model regarding mobility is set with professionals baring a 1.0% chance of dying each turn, laborers 1.3%, and criminals 3.0%.

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criminals.

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

The key to the experiment in question was the exogenous shock distributed to one of the regions in each simulation run. At turn 20, the northwest quadrant (Region 1) was hit with a mortality shock[12] that resulted in the death of 5% of its population. This shock then recurred each turn for 10 turns (20 - 29). "Shock" deaths were in addition to any deaths which occurred as result of the standard probabilistic algorithms.

4.1 Results

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).

4.1.1 The Children of Disaster

The mean[13] criminal percentage [Figure 2] is significantly higher in the shocked regions, and persists for the full 180 turns after the shock. The crime rate predictably goes up during the shock as youths arriving at age sixteen are heavily exposed to evidence that shortens their subjective life expectancy. 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 bares a disproportionate effect on their offspring which have remained in neighboring patches.

4.1.2 The Grandfather Effect

There are observable "bumps" in the shocked region, usually just one or two, fifty to one hundred 100 turns after the shock. An example can be found in Figure 1, the charted percentage of each region's population that has chosen the "criminal" occupation in the first[14] of 100 simulation runs. While we cannot directly infer anything substantial from one simulation run, it serves as a representative case[15].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.

[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] Median data was also tested and is available upon request. No significant difference was observed.
[14] Appendix A has three reprensentative runs for comparison
[15] 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 in. The data must be a confirmed as non-anomalous in general structure, but means and medians can "smooth away" useful information regarding how the artificial history plays out.

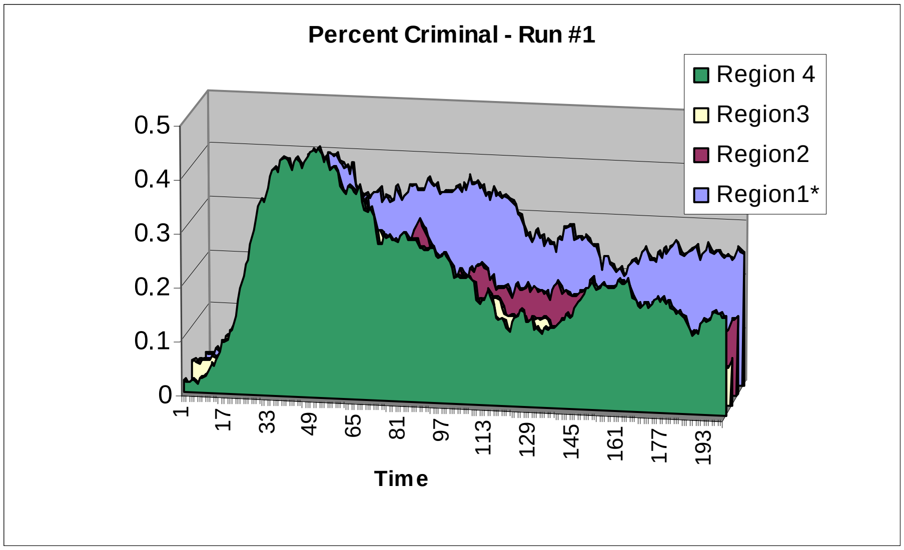

Figure 1 : Run #1 of 100, comparing all four regions. Region #1 experience a morbidity shock in from time 20 until time 29. Regions 2 - 4 were not shocked, but 2% of the adult population moved each turn

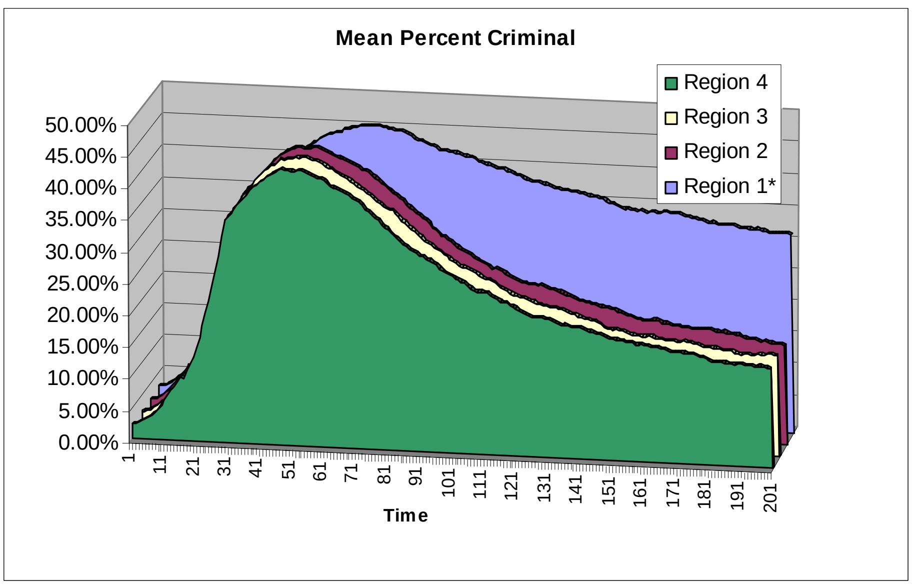

Figure 2 : Means across 100 runs, each consisting of 200 turns

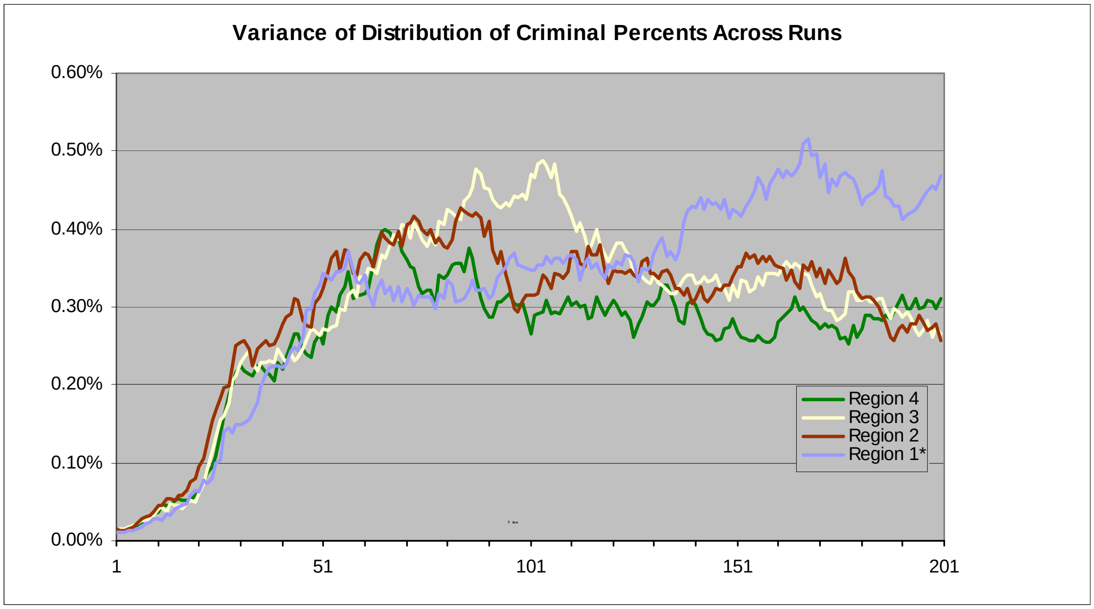

Figure 3 : Variance across 100 runs, each consisting of 200 turns

4.1.3 Diffusion of Criminals

As expected the crime rate explodes during the shock: the perceived life span plummets, people expect to die any day now 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.[16] Once the shock ends the crime rate begins to drop in the shocked region, while the non-shocked regions return to previous levels almost immediately.

4.2 Feasibility of Bounded Rationality

A 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 naturally tendency of the model is demonstrated to be a bias towards *overestimating* expected life, and away from criminal career choice.

Table 1 : Control Experiment

Turns Completed	50	100	150	200	250
Mean Differential (LE – ML)	-1.73	3.61	3.83	3.08	2.59
Percent Differential (Diff. / ML)	-3.64%	7.24%	7.52%	5.95%	4.96%

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

5 Conclusions

In a model such as CAMSIM an historical anomaly can act as the seed for future behavior that is, from standard methods of analysis, ostensibly irrational. Future efforts to validate the CAMSIM model and to extend and calibrate it to reality would have to exclude 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.[17] 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.

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[18]. 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.

As a final thought, it must be said that no matter how many times the model or experiments were run the ability for a single shock, which directly impacts no more than two generations, to persist through time never ceases to impress. It is a stark reminder that society is always a victim of its past, and that perhaps the social scientists that are most needed to jump into this amalgam of sociologists, economists, and psychologists are in fact historians.

[17] Though, again, it does not verify any of the parameters employed as calibrated to reality, nor does it suggest that CAMSIM is sufficiently specified.

[18] 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.

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References

Banfield, E. C. (1970). The unheavenly city; the nature and future of our urban crisis. Boston, Little Brown.

Becker, G. S. (1964). Human capital; a theoretical and empirical analysis, with special reference to education. New York,, National Bureau of Economic Research; distributed by Columbia University Press.

Becker, G. S. (1968). "Crime and Punishment: An Economic Approach." The Journal of Political Economy **76**(2): 169-217.

Behrman, J., L. Kletzer, et al. (1998). "Microeconomics of College Choice, Careers, and Wages." The Annals of the American Academy of Political and Social Science **559**(The Changing Educational Quality of the Workforce): 12-23.

Bottoms, A. E. (1997). Environmental Criminology. The Oxford Handbook of Criminology. R. M. Mike Maguire, and Robert Reiner. Oxford, Clarendon Press**:** 585-656.

Coleman, J. S. (1990). Foundations of Social Theory. Cambridge, The Belknap Press of Harvard University Press.

Cook, K. S. and M. Levi (1990). The Limits of rationality. Chicago, University of Chicago Press.

Corman, H. and H. N. Mocan (2000). "A Time-Series Analysis of Crime, Deterrence, and Drug Abuse in New York City." American Economic Review **90**(3): 584-604.

Denes-Raj, V. and H. Ehrlichman (1991). "Effects of Premature Parental Death on Subjective Life Expectancy, Death Anxiety, and Health Behavior." Omega **23**(4): 309-321.

Ehrlich, I. (1996). "Crime, Punishment, and the Market for Offenses." The Journal of Economic Perspectives **10**(1): 43-67.

Epstein, J. M., R. Axtell, et al. (1996). Growing artificial societies social science from the bottom up. Washington, D.C., Brookings Institution Press.

Farrington, D. P. and B. J. Knight (1979). "Two non-reactive field experiments on stealing from a "lost" letter." British Journal of Social and Criminal Psychology **18**: 277-284.

Ferri, E. (1898). Criminal sociology. New York,, D. Appleton and company.

Fisher, J. D., P. A. Bell, et al. (1984). Environmental psychology. New York, Holt Rinehart and Winston.

Gladwell, M. (2000). The tipping point : how little things can make a big difference. Boston ; London, Little Brown.

Glaeser, E. L. and B. Sacerdote (1999). "Why Is There More Crime in Cities?" Journal of Political Economy **107**(6, Part 2: Symposium on the Economic Analysis of Social Behavior in Honor of Gary S. Becker): S225-S258.

Hamermesh, D. S. (1985). "Expectations, Life Expectancy, and Economic Behavior." The Quarterly Journal of Economics **100**(2): 389-408.

Harries, K. D. (1973). The geography of crime and justice. New York,, McGraw-Hill.

Harries, K. D. (1980). Crime and the environment. Springfield, Ill., Thomas.

Herbert, D. T. (1982). The geography of urban crime. London ; New York, Longman.

Kahneman, D., P. Slovic, et al. (1982). Judgment Under Uncertainty: Heuristics and Biases. Cambridge, Cambridge University Press.

Keane, M. P. and K. I. Wolpin (1997). "The Career Decisions of Young Men." Journal of Political Economy **105**(3): 473-522.

Kelling, G. L. and National Institute of Justice (U.S.) (1999). "Broken windows" and police discretion. Washington, DC, U.S. Dept. of Justice Office of Justice Programs National Institute of Justice.

LaFree, G. (1999). "Declining Violent Crime Rates in the 1990s: Predicting Crime Booms and Busts." Annual Review of Sociology **25**: 145-168.

MacDonald, W. L. (1998). Secularization in the United States: Scientific versus Religious Authority. American Sociological Association Meeting.

Mathur, V. K. (1978). "Economics of Crime: An Investigation of the Deterrent Hypothesis for Urban Areas." The Review of Economic Statistics **60**(3): 459-466.
McCloskey, D. N. (1996). The vices of economists, the virtues of the bourgeoisie. Amsterdam, Amsterdam University Press.
McCloskey, D. N. (1998). The rhetoric of economics. Madison, Wis., University of Wisconsin Press.
Nam, C. B. and T. M. Harrington (1986). Factors Shaping the Morbidity-Mortality Expectations of Youth: A Socialization Model. Fertility and mortality : theory, methodology, and empirical issues. K. Mahadevan, P. J. Reddy and D. A. Naidu. New Delhi ; Beverly Hills, Sage Publications**:** 351.
Nelson, L. d. and J. A. Honnold (1980). "Socialization and Demographic Determinants of Mortality Expectations." Population and Environment **3**(1): 10-22.
Parsons, T. (1949). The structure of social action; a study in social theory with special reference to a group of recent European writers. Glencoe, Ill.,, Free Press.
Philipson, T. J. and R. A. Posner (1996). "The Economic Epidemiology of Crime." Journal of Law and Economics **39**(2): 405-433.
Potts, J. (2000). The new evolutionary microeconomics : complexity, competence, and adaptive behaviour. Cheltenham, UK ; Northampton, MA, E. Elgar Pub.
Schelling, T. C. (1978). Micromotives and Macrobehavior. New York, W. W. Norton Company.
Shaw, C. R. and H. D. McKay (1942). Juvenile delinquency and urban areas, a study of rates of delinquents in relation to differential characteristics of local communities in American cities. Chicago, Ill.,, The University of Chicago Press.
Simon, H. A. (1955). "A Behavioral Model of Rational Choice." The Quarterly Journal of Economics **69**(1): 99-118.
Simon, H. A. (1956). "Rational Choice and the Structure of the Environment." Psychological Review **63**(2): 129-138.
Simon, H. A. (1959). "Theories of Decision-Making in Economics and Behavioral Science." The American Economic Review **49**(3): 253-283.
Simon, H. A. (1982). Models of bounded rationality. Cambridge, Mass., MIT Press.
Simon, H. A. (1986). "Rationality in Psychology and Economics." Journal of Business **59**(4, Part 2: The Behavioral Foundations of Economic Theory): S209-S224.
Smith, A. (1981 [1776]). An inquiry into the nature and causes of the wealth of nations. Indianapolis, Liberty Classics.
Swedberg, R. (1990). Economics and Sociology. Redifining their Boundaries: Conversations with Economists and Sociologists. Princeton, Princeton University Press.
Taylor, R. B. (2001). Breaking away from broken windows : Baltimore neighborhoods and the nationwide fight against crime, grime, fear, and decline. Boulder, Colo., Westview Press.
Teahan, J. and R. Kastenbaum (1970). "Subjective Life Expectancy and Future Time Perspective as Predictors of Job Success in the "Hard-Core" Unemployed." Omega 1: 189-200.
Trumbull, W. N. (1989). "Estimations of the Economic Model of Crime Using Aggregate and Individual Level Data." Southern Economic Journal 56(2): 423-439.
Wilensky, U. (1999). NetLogo, Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.
Wilson, J. Q. and R. J. Herrnstein (1985). Crime and human nature. New York, Simon and Schuster.
Wilson, J. Q. and G. Kelling (1982). "Broken Windows: The Police and Neighborhood Safety." Atlantic Monthly: 29-38.