The Analysis of the General Decline in U.S. Crime Rates since the Mid-1990s: The Multiplier Effects of Dynamic Social Interactions in a Model of Belief Convergence

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Abstract

Regardless of the long debate over why U.S. crime rates fell so rapidly and generally since the mid-1990s, the question is still unsettled. While the nationwide legalization of abortion in 1973 and the consequent reduction in the number of juveniles seems to have caused the rapid decline in crime rates in the 1990s. However, the puzzle of the decline in a variety of crimes, especially those committed by adults, remains unanswered. This paper attempts to provide the framework for understanding how a number of small changes in the social network could generate huge multiplier effects and could explain the general downward trend of U.S. crime rates over the decade. In this paper, I propose a Belief Convergence Model, in which the dynamic shifts of people's preferences as a result of information exchange in social interactions causes a significant adjustment of beliefs for all participants within the network over the long run. This implies that a variety of socioeconomic changes must have had a larger positive externality than scholars have estimated in their research papers.

"What is a friend? A single soul dwelling in two bodies" -Aristotle

I. The U.S. Crime Trend since the Mid-1990s

Overall U.S. crime rates began to fall rapidly during the mid-1990s. The U.S. total violent crime victimization rate was 51.190 per 1,000 households in 1994 but had dropped to 22.30 per 1,000 households in 2003 (Appendix I). The U.S. property crime victimization rate, which has continuously declined since its peak in the 1970s, also began to fall sharply in the mid-1990s (Appendix II). Furthermore, Uniform Crime Reports (UCR) for the first six months of 2004 estimates a further 2.0% decline in violent crime and a 1.9% decline in property crime. Just a few decades ago, no one, including criminologists such as James Alan Fox (1978), could imagine future U.S. crime rates dropping so dramatically.

While the downward trend of recent U.S. crime rates is apparent, there has been a debate over its cause. In Section II, I briefly discuss a variety of possible explanations for the general decline of U.S. crime rates. The majority of Section III is spent explaining the work of Levitt and Donohue (2000) on the impact of abortion on U.S. crime rates. Section IV introduces a Belief Convergence Model (BCM) along with a set of plausible patterns of social interaction to describe information transfer among people in the network. The interpretations of this model and three example cases are provided in Section V, in which I discuss the applicability of BCM to the decline of crime rates in the U.S. as well as a wide range of other topics in criminology.

II. Brief Overview of Hypothesis in Cross-National Studies in Crime and Justice

Cross-National Studies in Crime and Justice, published by U.S. Department of Justice in September 2004, states, "In summary, falling rates of crime were most consistently related to the aging of the population and to falling unemployment rates and rising risk of punishment by the justice system."(68.) A number of similar discussions and explanations have frequently been seen even outside of academic journals[1].

How valid are these arguments? To begin with, American society is indeed aging, as the Baby Boomers grow older[2]. This demographic shift is significant because of the disproportionate number of criminals in younger age brackets. Appendixes III and IV show that young people, especially those between 18 and 24, are the most prone to commit a crime and most likely to become victims as well[3], i.e. there is a strong correlation between the number of young people and the crime level. As Fox (1978) describes, "The sizable increases in the crime rate during the 1960s appear to be largely a result of a perturbation in the birth rate during the postwar years" (77). Appendix V shows that periods of high fertility rates preceded by approximately 20 years the skyrocketing crime rates of the 30s and the 60s to 70s. It also shows a decline in fertility rates during the 1970s and the subsequent aging of the population in the United States, which must have contributed to the general fall in crime rates.

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[1] See, for example, McIntyre (2000) <http://www.bos.frb.org/economic/nerr/rr2000/q1/mcin00_1.htm> and Fletcher (2000) < http://www.eisenhowerfoundation.org/aboutus/media/WashPostCrimeConumdrum_Jan16.html> for their brief overviews of various explanations and counter arguments to falling crime rates.

[2] U.S. National Institute on Aging. "Aging in the United States. -Past, Present, and Future-."

[3] See "Age-Specific Arrest Rates and Race-Specific Arrest Rates for Selected Offenses 1993-2001" <http://www.fbi.gov/ucr/adducr/age_race_specific.pdf>

The impact of two other factors on crime rates - falling unemployment and the rising risk of punishment by the justice system – can be largely explained using Becker's Rational Choice Theory (1986). This is considered a pioneering work in the modern economic analysis of crime. In Becker's view, criminals are no different than ordinary consumers; they are assumed to be rational and to make choices based on an analysis of the costs and benefits of committing a crime. Thus, Becker's theory predicts that one would commit a crime if

$$w \leq b(x) - p(x)*f(x) \qquad (1)$$

where

w = opportunity cost (usually one's legitimate wage)

b = benefits of committing a crime,

p = probability of being arrested

f = severity of punishment and future opportunity costs.

x = the severity of crime where b, p, and f are functions of x

According to Becker, a utility-maximizing criminal chooses the level of crime where marginal cost is equal to marginal benefit. The first derivative shows that crime increases when w goes down, b goes up, p or f goes down, or any combination of these occurs. It is worth noticing that Becker suggests that the low value of p will be offset by the large enough value of f. So, setting the severity of punishment intentionally high creates the deterrence effect that cancels out the inefficiency or shortage of policing, making it less costly for the government to combat crime. Consistent with this idea, Grogger (1991), Levitt (1997), Ayres and Levitt (1997), Levitt (1998) and Mocan and Ress (1999) find a negative correlation between punishment and crime rates and conclude that punishment has a deterrence effect.

During the 1990s, Americans experienced economic prosperity. However, there is an argument over how or even whether a change in general economic prosperity affects crime rates. While Freeman (1991) finds the positive correlation between the chance of going to jail and living standard, Witte (1980) finds that crime declines as unemployment rises. In fact, Freeman (1995) finds that economic prosperity is not correlated with crime rates.

One explanation could be that when people become rich, usually the payoffs for criminals also rise. Likewise, an economic downturn lowers the returns from burglary and the sale of illegal drugs. Thus, it was very likely that b in Becker's model rose as well during the economic boom in the 1990s. As Gould and Weinberg (1999) discuss, wage growth or economic prosperity in general needs to be observed with sophisticated techniques to separate the endogenous problems from that which you wish to observe.

Furthermore, most Americans did not see the economic success of the 1990s reflected in their incomes. In terms of CPI-U-RS Adjusted Dollars, median household income increased only 10% from 1993 to 2003[4]. It is true that the poverty rate for families improved during the same period and dropped from its highest level in the 1990s of 12.3% in 1993, on the eve of a sudden decline in crime rates, to its lowest level of 8.7% in 2000. It is also true that the average poverty rate for families with female heads of households in the 70s was 32.24%, while the rate between 1994 and 2003 was 29.52%.

[4] U.S. Census Bureau. "Historic Income Table"
<http://www.census.gov/hhes/www/income/histinc/h13.html>

Yet, Cross-National Studies in Crime and Justice (2004) reports that this is still not a significant enough change to explain the general downward trend of crime rates.

On the other hand, the strong impact of a booming economy is shown in the change in unemployment rates. Unemployment fell dramatically in the 1990s, especially during the era of the dot-com bubble. According to Bureau of Labor Statistics[5], the national unemployment rate for people aged 16 years and over dropped from 5.6%[6] in 1995 to 3.97% in 2000, a decline of nearly 30% in just 5 years. For those between 16 and 19 years old, the unemployment rate also dropped from 17.34% to 13.08% for the same period, a 24.57% decline over 5 years. Since the legitimate wage, w in Becker's model, increased substantially, the Rational Choice Theory predicts the general decline of crime rates during this period, although this should have increased the returns from committing a crime to some extent..

While the opportunity cost of committing crimes seems to have increased, the cost of committing crimes may have also increased. We see neither a significant quantitative change in government and judicial expenditures (Appendix VI and VII), nor an explanatory qualitative change in the effectiveness of policing as shown by the arrest rates in Butts (2000). However, an increase in the severity of punishment in the 90s should have had a negative impact on crime rates. In fact, the "justice system became less lenient in its response to homicide" (the Cross-National Studies, 67) during the 1990s. This and newly adopted harsh policies such as so-called "three strikes" laws and the transfer of some juveniles to adult court in various states made people aware of the

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[5] U.S. Department of Labor, Bureau of Statistics, "Labor Force Statistics from the Current Population Survey"

[6] All the percentages I use here were derived from monthly data by averaging them for each year data were collected.

increasing cost of committing crimes. As a result of these policies, the population under correctional supervision increased annually by almost 3% between 1994 and 2003[7] while the annual U.S. population growth for the same period was slightly over 1%.

In summary, the conclusion made by Cross-National Studies in Crime and Justice (2004) appears to reflect what happened over the decade. The deterrence effects mentioned in the report should have resulted in generally falling crime rates to some extent, yet the sum of the deterrence effects is still not large enough. Some form of social multiplier effect is required to explain the general decline in crime rates, but even this cannot explain why U.S. crime rates fell so sharply, except a possibility that simply locking up habitual offenders might have sharply reduced the crime rate irrespective of individual perception.

III. The Impact of Demographic Changes due to Abortion on the U.S. Crime Rates

Donohue and Levitt address this puzzle by paying attention to the disproportionate age distribution of criminals in the population. In their controversial paper, which came out in the late 1990s, they state that there is a causal relationship between the legalization of abortion in the early 70s and the reduction of crimes in the 90s. They say, "The Supreme Court's 1973 decision in Roe v. Wade legalizing abortion nationwide potentially fits the criteria for explaining a large, abrupt, continuing decrease in crime" (Donohue and Levitt. 2).

[7] See Bureau of Justice Statistics < http://www.ojp.usdoj.gov/bjs/glance/tables/corr2tab.htm> (May 4, 2005)

The first evidence provided in their paper is the number of abortions. "Seven years after *Roe v. Wade*, over 1.6 million abortions were being performed annually; almost one abortion for every two live births" (Donohue and Levitt. 2). Taking it literally, there were 33% fewer young people in the 90s than there would have been otherwise, therefore lowering crime rates substantially.

Another piece of evidence that is even stronger is that the population distribution of those who are more likely to become criminals or to have abortions is not uniform. Donohue and Levitt argue that abortion is more likely to be chosen by teenage, unmarried, or economically disadvantaged females and that, therefore, the decrease in the numbers of females with unwanted children and young people in undesirable family environments should have caused a decrease in crime rates.

As the ultimate evidence for the connection between crime and abortion, Donohue and Levitt provide the result of their empirical analysis, which shows that those five states that adopted abortion earlier than the majority of other states also experienced an earlier rapid decline in crime rates. Thus, Donohue and Levitt conclude, "Indeed, legalized abortion may account for as much as one-half of the overall crime reduction" (Donohue and Levitt. 34).

However, even if this striking, novel idea by Levitt and Donohue explains the sharp reduction of crime rates to a large extent, we are still left with the need to explain the causation of the remaining fifty percent of the downward crime trend. Yet, it seems that the deterrence effects of socioeconomic changes discussed in Section II do not contribute all of the remaining fifty percent. More importantly, Appendix VIII, Victim's Perception of the Age of the Offender in Serious Violent Crime, shows that crime committed by adults also dropped by the same ratio as crimes committed by juveniles. Abortions conducted in between 1970 and 1973 could have removed crime-prone individuals only 24 year-old or younger at the time of 1994. So the cost-benefit and demographic analyses of crime taken together still do not adequately explain the puzzling general decline in crime rates across ages and types of crimes.

IV. The Dynamic Social Interaction, Discounting, and Belief Convergence Model

Summing up all the analyses, we still do not find a satisfactory answer to the question: Why did U.S. crime rates drop so sharply and, especially *generally*, in the 90s? What else could explain this puzzle in the analysis of crime rates? With the emergence of the new social economics theories, people are paying closer attention to the role of social interaction in the network effect, where individual behavior is dynamically influenced by actions taken by other members in the network. Reiss (1986) points out that youth behavior is negatively influenced by the absence of family, and often parental, control or by a disorganized social structure. Similarly, Case and Katz (1991) examine criminal activity and find that there is a positive correlation between the behaviors of individuals and their peers. Moreover, the Moving to Opportunity[8] (MOT) experiments and reviews of them[9] show that juvenile crime in fact dropped when families relocated from high- to low-poverty neighborhoods. However, the common problem in their works, including

[8] "Moving to Opportunity for Fair Housing (MTO) is a 10-year research demonstration that combines tenant-based rental assistance with housing counseling to help very low-income families move from poverty-stricken urban areas to low-poverty neighborhoods." U. S. Department of Housing and Urban Development <http://www.hud.gov/progdesc/mto.cfm>
[9] See, for instance, Duncan, Hirschfield, and Ludwig (2000)

the conformity effect argued by Young (2001) is that they do not provide satisfactory reasons as to why individuals should act in this manner.

In my view, social interactions play an important role in decision-making, in that individuals update their beliefs through the learning process of observing other people's behaviors, sharing experiences with others, and obtaining new information from various sources. That is, people learn in each period how they should act in the next period. Economic agents usually have imperfect, asymmetric information, therefore the utilization of information is very important to their decision-making processes. The mathematical process of such belief updating can be expressed by Bayes Theorem:

$$P(F|E) = [P(E|F)/\{P(E|F)*P(E)+P(E|F_c)*P(F_c)\}]P(F) \quad (3)$$ [10]

In plain language, this means that you can obtain your posterior belief by updating your prior belief with new information. Suppose you believe you have a fifty-fifty chance of being arrested after committing a certain crime. When your friends tell you that the chance is much higher, you will consider the risk more seriously than before.

However, in the real world people do not take new information as it is given. In other words, credibility, persistency, and other factors become obstacles to updating one's prior beliefs. Thus, bias is another important factor to explain whether one will underestimate or overestimate the benefits and costs of crimes. The sources of bias include, but are not limited to, the credibility of an information source, religious beliefs, norms, persistency, and internal chemical stimuli. The mathematical notation for such an updating process with bias can be expressed as

[10] A little c means a negation.

One's Posterior Belief = α*(One's Prior Belief) + (1- α)*(New Information) (4)[11]

Note that one's posterior belief is bounded between one's prior belief and a value given through new information. This is intuitive because if you think the value of your 2000 Honda Accord is $15,000 and your friend thinks it is $10,000, the value in your mind should be somewhere between those two values but should not jump to $25,000 or drop to $5,000. Likewise, the commission of a crime becomes more appealing and the apparent benefit of crime increases when your accomplice underestimates the costs of committing a crime or overestimates its benefits.

Another important idea that has recently gotten the attention of economists is discounting. Committing a crime comes with great uncertainty. For instance, a burglar wouldn't know exactly how much he or she would get by attacking a pedestrian chosen on the street randomly nor the exact length of imprisonment and its effect on his or her career if arrested. This is one of the reasons why most people are impatient and discount the future relative to the present[12].

Cooter (1998) supposes that a person receives a benefit from committing a crime at time 1, shown as b_1, and will receive punishment in the future, c_2. r represents the individual specific discount rate. His model, based on Becker's Rational Choice Theory, predicts that

[11] $0 \leq \alpha \leq 1$

[12] Such excessive myopia, the miscalculation of future utility, has been observed with a unique property, described as hyperbolic discounting. For the exact mechanism of discounting and application in the time series analysis, one should refer to Battaglini, Benabou, and Tirole (2003) and O'Donoghue and Rabin (2000). On the other hand, in this paper I use a simple discounting model like Cooter (1998) uses to explain the individual specific discount rate based on morality in decision making. Fortunately, this simplification of the analysis does not make a crucial difference in the results.

$$b_1 - (c_2/r) \geq 0 \rightarrow \text{commit a crime}$$

$$b_1 - (c_2/r) \leq 0 \rightarrow \text{do not commit a crime} \quad (5)$$

Then, there is some $r = r^*$ such that:

$$b_1 - (c_2 / r^*) = 0 \quad (6)$$

or equivalently,

$$r^* = c_2 / b_1 \quad (7)$$

Thus, the person commits a crime when r is greater than r*, and this can be shown with an individual specific probability distribution for committing a crime. This individual specific model implies that the real value of crimes is not necessarily equal to the real cost of crime. In other words, if r* is large, then there is a smaller probability of committing a crime, therefore fewer crimes, and if r* is small, then there will be a larger probability of committing a crime, therefore more crimes. This model connects the distribution of r to lapses in judgment, yet it lacks an explanation as to how and why r moves.

The Belief Convergence Model combine these two aspects, information update processes and discounting, and sets up a simple network to see how this discounting value is determined through the social interactions. Suppose there is a group within a network composed of n individuals. Call this pool of people M and m = 1, 2, 3, …, n. Each period represents a social interaction of individuals selected from M. Furthermore, assume that R represents the discount value on the cost of committing a crime, which is derived from all kinds of discount factors such as imperfect information or psychological effects. Also, each player has an initial value of R. Call a player with $R > 1$ an Optimist (O), a player with $R = 1$ a Neutralist (N), and a player with $R < 1$ a Pessimist (P). An Optimist will tend to discount the cost of committing a crime and thus will be more likely to commit a crime than a Neutralist.

Using the equation (4), we have

$$\text{One's Posterior Belief} = \alpha^*(\text{One's Prior Belief}) + (1-\alpha)^*(\text{New Information})$$

This equation can be rewritten as a Belief Convergence Model (BCM) with time periods below

$$R_{m,t} = \sum_{i=1 \text{ and up to } n} (\alpha_{m,i,t})^*(R_{i,t-1})$$
$$\text{where } \sum_{i=1 \text{ and up to } n} (\alpha_{m,i,t}) = 1 \qquad (8)$$

$R_{m,t}$ is m's discount rate at period t, and $\alpha_{m,i,t}$ is m's confidence in i about the accuracy of the value of $R_{i,t-1}$ at period t. So, if two people, A and B, from M interact, the BCM above say

$$R_{A,t} = (\alpha_{A,A,t})^*(R_{A,t-1}) + (1-\alpha_{A,A,t})^*(R_{B,t-1}) \qquad (9)$$
$$R_{B,t} = (\alpha_{B,B,t})^*(R_{B,t-1}) + (1-\alpha_{B,B,t})^*(R_{A,t-1}) \qquad (10)$$

In every situation where A and B interact and exchange information, they both decide their own weights of belief in the other person's information: namely $\alpha_{A,B,t} = (1- \alpha_{A,A,t})$ and $\alpha_{B,A,t} = (1- \alpha_{B,B,t})$ where both are distributed between 0 and 1. After each period, they update their own Rs and move on to the next period in which each player will choose a new confidence parameter value, α.

It is important to know this equation shows linear recurrence relations for multi-variables. For instance, (9) can be expressed as

$$R_{A,t} = (\alpha_{A,A,t})*\{(\alpha_{A,A,t-1})*(R_{A,t-2}) + (1- \alpha_{A,A,t-1})*(R_{B,t-2})\}$$
$$+ (1- \alpha_{A,A,t})*\{(\alpha_{B,B,t-1})*(R_{B,t-2}) + (1- \alpha_{B,B,t-1})*(R_{A,t-2})\} \quad (11)$$

That is, the past values of R affect the future values of R forever. It is also important to note that this series converges to some value when t goes to infinity, given that none of the confidence parameters can be 1 or 0 at the same time. In other words, if t is large enough, $R_{A,t}$ becomes arbitrarily close to $R_{B,t}$. Suppose $R_{A,t-1} > R_{B,t-1}$ and $0 < \alpha_{A,A,t} < 1$. Factoring out (9), we have

$$R_{A,t} = (\alpha_{A,A,t})*(R_{A,t-1}) + (R_{B,t-1}) - (\alpha_{A,A,t})*(R_{B,t-1})$$
$$= (\alpha_{A,A,t})*(R_{A,t-1} - R_{B,t-1}) + (R_{B,t-1}) \quad (12)$$

Since $(\alpha_{A,A,t})*(R_{A,t-1} - R_{B,t-1})$ is positive, $R_{A,t} > R_{B,t-1}$ must be true.

Subtracting ($R_{B,t-1}$) from both sides in (12) shows

$$(R_{A,t} - R_{B,t-1}) = (\alpha_{A,A,t})*(R_{A,t-1} - R_{B,t-1}) \qquad (13)$$

The difference between $R_{A,t-1}$ and $R_{B,t-1}$ is larger than the difference between $R_{A,t}$ and $R_{B,t-1}$, therefore $R_{A,t-1}$ must be greater than $R_{A,t}$. Since $R_{A,t-1} > R_{A,t} > R_{B,t-1}$, and one's discount rate is always bounded between ones' previous discount rate and the other's previous discount rate. Thus, the $R_{A,t+n}$ and $R_{B,t+n}$ will converge to the same value if n is large enough.

CASE 1: Social Interaction between Friends A and B

There are two individuals in this case: A and B. One generally has more confidence in one's own estimates than in those of others. So, in this two-people setting, both $\alpha_{A,A,t}$ and $\alpha_{B,B,t}$ are randomly distributed between .8 and 1. Moreover, their initial Rs are set to $R_{A,0}$ = 1.5 and $R_{B,0}$ = .85, and are characterized as O and P in period 0. Random variables for the confidence parameters were generated using Excel and assigned to each player for each period.

The results of this simulation are shown in Appendix IX. After 20 interactions, we see the tendency; R_A and R_B seem to be converging at somewhere slightly over 1.1. Thus, B who was originally P turned to be O in this case, therefore committing more crimes than before. Note also that R_A and R_B is bounded between 1.5 and .825. The convergence in this case shows that spending enough time together causes these individuals to share the same estimation about the benefits and costs of committing a crime. As a consequence, A and B behave as if they are “a single soul dwelling in two bodies.”

Case II: Parent and Child: B and C

In this case, there are also two individuals: B and a new person, C, selected from M. However, C is B’s parent so that C has high confidence in C’s $R_{C,t}$ and B has low confidence in $R_{B,t}$. Let $\alpha_{C,C,t}$ be distributed between .9 and 1 and $\alpha_{B,B,t}$ be always between 0 and .2.

Appendix X shows that R_B and R_C have already converged to .984 by the second period. Readers should also note that there is no way for j or k to be considered as O or N in this case because initial R_B or R_C are both lower than 1.

CASE III: Child, Child’s friend, and Parent[13]: A, B, and C

All the individuals from the previous cases with the same confidence parameters are participating in this case: A, B, and C. Every three times B interacts with A, B interacts with C. The interpretation of this setting is a child who goes to school and spends a lot of time with his or her friend during the daytime but comes back home and talks to the parent in the evening.

In Appendix XI, non-interacting individuals are isolated from the BCM and are shown in the gray zones. There are three interesting results in this case. First of all, B changes from P to O in the first period but changes from O back to P in the fourth period and from P to back to O in the fifth period. Another interesting outcome is that A now

[13] For this multiplayer pattern, it is possible for all of A, B, and C to interact in the same period. Then, the equation will still follow the BCM.

has a lower R than before (also that C has a higher R than before). Also, by the 20th period, three of them have not quite reached the converging pint yet.

Note that BCM does not discriminate any source of information in the network. I set up the network only with the social interactions among real people in the past examples, but the interaction and information exchange with non-living entities in the network is also possible. This in fact occurs everywhere in the real world. For example, the exchange of information between you and the law is one way; the law can alter your behavior by telling you exactly what you can and can't do and the level of punishment, but not the other way around. This is the extreme version of Case II: Parent and Child where Child is almost subordinate in terms of confidence. Likewise, you will immediately come to realize your overestimation or underestimation of the value of a certain activity by becoming aware of the law. This has a deterrence effect on crime as Cooter (2004) argues that frequent small punishments or parental control is sometimes more effective than a one-time large punishment such as the death penalty because the deterrence effect of punishment is inefficacious when R, the multiplicative discount factor, is high, as in our model[14].

V. The Interpretations of the Simulations and the Applicability of BCM to Crime Analysis

[14] On the other hand, there is an undesirable case of $\alpha_{i,t} = 1$ in society as well. Imagine the advertisement or TV program with violent contents. Although the characters are pure objects and do not respond to what you think, they still project some messages into the network, in which real people are likely to have a confidence parameter less than 1. The model predicts that R for an individual being surrounded by such contents will converge to the high value of R.

In the previous simulations, the exchange of information through social interactions among people did influence their decision-making. This aspect is crucial to understanding the impact of social multiplier effects on crime rates. To begin with, assume that the network has a finite, fixed number of people with different values of initial Rs in some given period. If $\alpha_{m,m,,T}$[15] is equal to 1, all of the individuals will maintain their own initial Rs since no one trusts external information. On the other hand, if $\alpha_{m,m,,T}$ is equal to 0, people will always adopt other people's Rs whenever there is an interaction, therefore there will be no equilibrium. In a more realistic situation where people have $0 < \alpha_{m,m,,T} < 1$, there is only one equilibrium due to the convergence. Theoretically, people in the network will eventually share the same value of R no matter how many people there are.

However, the observed R often fluctuates dynamically rather than at the equilibrium. Appendix XII shows how each individual's R behaves in social interactions in Case III. Notice the trends in the graph. The stochastic dynamic linear simulation clearly shows the changing level of the mean, a decreasing variance, and autocorrelation for each R. This changing mean is, in fact, the fluctuation of r in Cooter's model discussed before[16]. Under the influence of peers possessing high discounting values, a child would behave much more carelessly than usual. However, in the evening, free from their influence and in a different network, he may realize how silly his actions were.

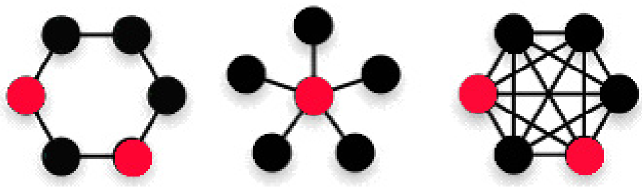
While the relationship between the convergence and a decreasing variance of R in Case III can be easily predicted, the upward or downward trend of R depends on which individuals interact each other. In the graph, an obvious seasonality for each R results

[15] m's belief in m's R at T where m = 1, 2, 3, … n and T = 1,2,3, ….,t
[16] See Cooter's "Saturday Night Fever" (2004)

from the repeated social interaction patterns of A, B, and C. Since R in period t is bounded between two Rs in period t-1, it is easy to predict whether R will rise or not once we know which two people are having a social interaction.

This indicates why the existence of female-headed households and gangs in the community can be risk factors for increasing crime rates. Glaeser and Sacerdote (1996) use the logarithmic regression model to analyze the city-crime connection based on the 1994 Statistical Abstract of the United States. They conclude that 45 % of the connection can be explained by the lower number of intact families found in cities. Applying the BCM model, since single parents have less time to spend with their children, their children' discount rates are often bounded between theirs and their peers', both of which are usually much higher than adults' Rs. For similar reasons, when youths form a gang, the shared discount rate will be very likely to be bounded between some high Rs.

Network topology makes the analysis of such a group of people easy. Suppose dots in the graph below represent individuals in the network. The lines show which ones are connected to one another, and any unconnected dots are not in the same network, therefore there are three separate networks. If two red dots in the ring network (on the left) cut the connection to their neighbors on either side, the ring network will be divided into two line networks, each of which has a unique equilibrium. In the star network shown in the center, if the red central dot refuses to connect to any of the other people, then there will be 6 networks, each of which is composed of just one dot. In the more complicated network, even if two red dots in the network cut the connection to one of their neighbors, there will still be only one equilibrium.



This phenomenon may be considered as a multiplicity of equilibria in crime rates with the same economic fundamentals (Calvo-Armengol and Yves Zenou, 2003) or the spatial differentiation in crime rates within the small area such as Manhattan. Theoretical analyses of Schelling (1971), Young (2001), and Axtell, Epstein, and Young (2001) explain that people should have preferences about where to live and whom to live close to. So, theoretically, people should relocate themselves in order to maximize their utility. Using data collected from 127 populous U.S. cities, Cullen and Levitt (1999) study[17] the impact of crime on mobility and find that, in fact, those households with relatively high levels of education or with children move more readily in response to crimes. Moreover, they also find that "rising city crime rates are causally linked to city depopulation" (167). This empirical study also shows that poor residents are more likely to remain in the ghetto than are those who have the means of moving out.

These asymmetric opportunities for people to decide where to live and with whom to live create residential segregation as well as social segregation. For instance, in spite of the physical proximity between wealthy residents and poor residents in cities, they are often socially distant. They attend different schools and live in different blocks. Since such social segregation creates many sub-networks within the whole network, the BCM

[17] Julie Berry Cullen and Steven D. Levitt. "Crime, Urban Flight, and The Consequences for Cities." The Review of Economics and Statistics. (May 1999) Number 2. (159-169)

predicts that some groups are more likely to have high discounting rates than other groups.

Akerlof (1997) reaches a very similar conclusion; given multiple equilibria, some people are more prone to be trapped in a low equilibrium than other people. In his Conformist Model, individuals look for the minimization of social distance between themselves and other people. In other words, people are assumed to have disutility by deviating from other people. Then, one's utility is given as

$$U = -\,d|x - x_{tilda}| - ax^2 + bx + c \quad (14)$$

where

d = the taste for conformity

x = one's choice

x_{tilda} = the choice of everyone else

Thus, if everyone is alike, x must be equal to x_{tilda}. In this model, it can be easily observed that there are multiple possible equilibria whenever d is greater than zero, depending upon initial endowments. Since people choose their actions to be the same as others', social distance is getting smaller and smaller just like the convergence in BCM[18].

These properties of the BCM and the network topology reveal the applicability of the BCM to the analysis of the overall decline of U.S. crime rates since the mid-1990s. . Since any individual within the network influences all other members to some extent, the

[18] The Conformist Model is not an alternative explanation of BCM but should probably be combined with BCM. In the analysis of crime, one's willingness to minimize the social distance between oneself and other embers within a network explains only part of the whole utility. On the other hand, this conformity effect seems to be as important as the learning process in social interaction.

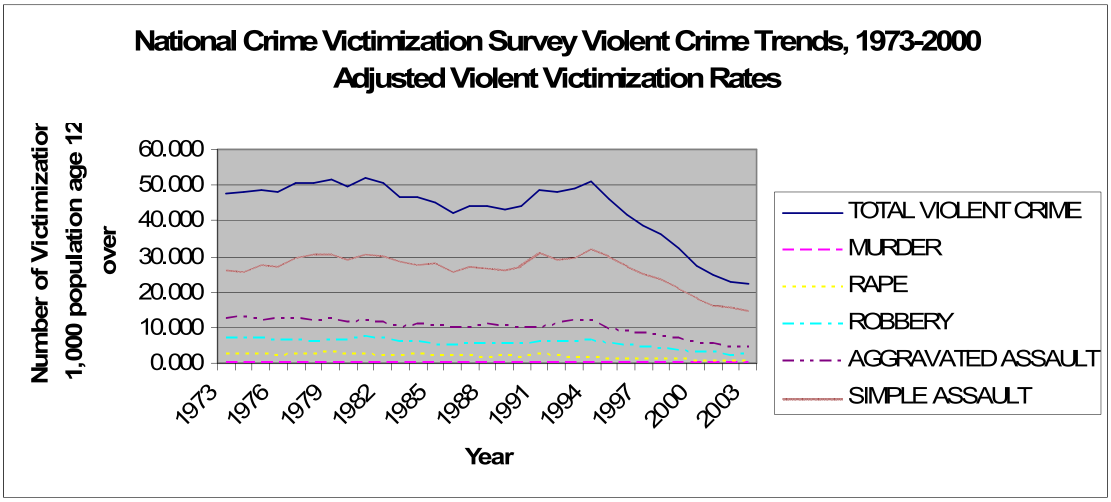
positive effects happening in some part of the network would be transferred to other parts of the network as well through social interactions. So, a variety of socioeconomic variables discussed in Section II and III could have created the positive externality within the network. More importantly, the rapid decline of the number of crime prone individuals due to legalized abortion must have significantly lowered the equilibrium value of R within networks, , therefore the causing the decline in crime rates not only among juveniles but also among adults. Thus, such social multiplier effects could explain the general decline in crime rates in the past 10 years.

VI. Conclusion

The puzzling fall in U.S. crime rates must have had a variety of causes, but scholars argue that no theory so far has satisfactorily explained two properties of the decline in crime rates: speed and generality. While abortion seems to explain the rapid decline in crime rates that began in the mid-1990s, the Belief Convergence Model may provide an answer to the general decline in U.S. crime rates for the past 10 years. Still, there is a need for the empirical research to test how and to what extent changes in belief could have influenced crime rates. In such a research, as Kling, Ludwig, and Katz (2004) find in their analysis of youth behavior and crime that males and females adopt and respond to new neighborhood environments differently, the careful treatment of both exogeneity and endogeneity that are not captured in BCM becomes an important issue.

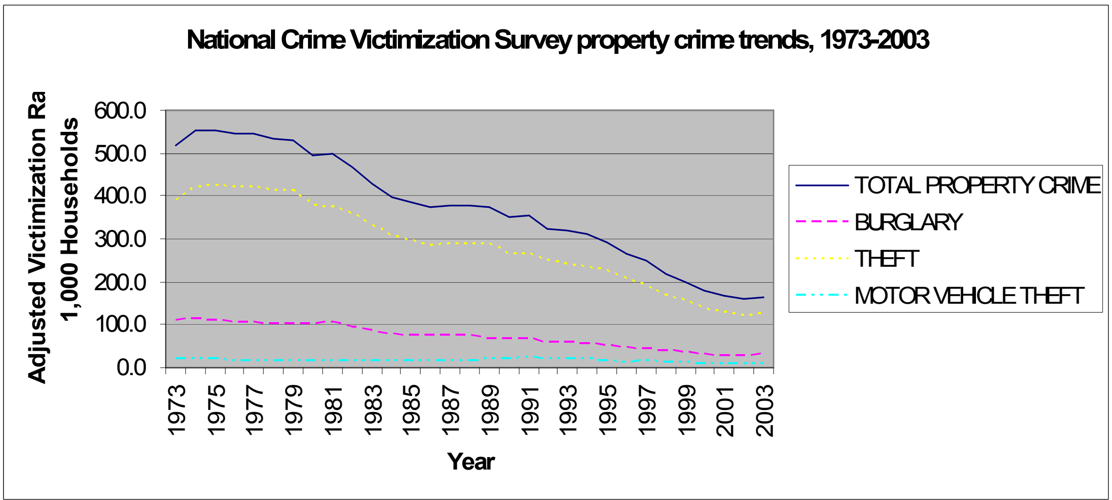
Appendix

Appendix I: Violent Crime Victimization Rates



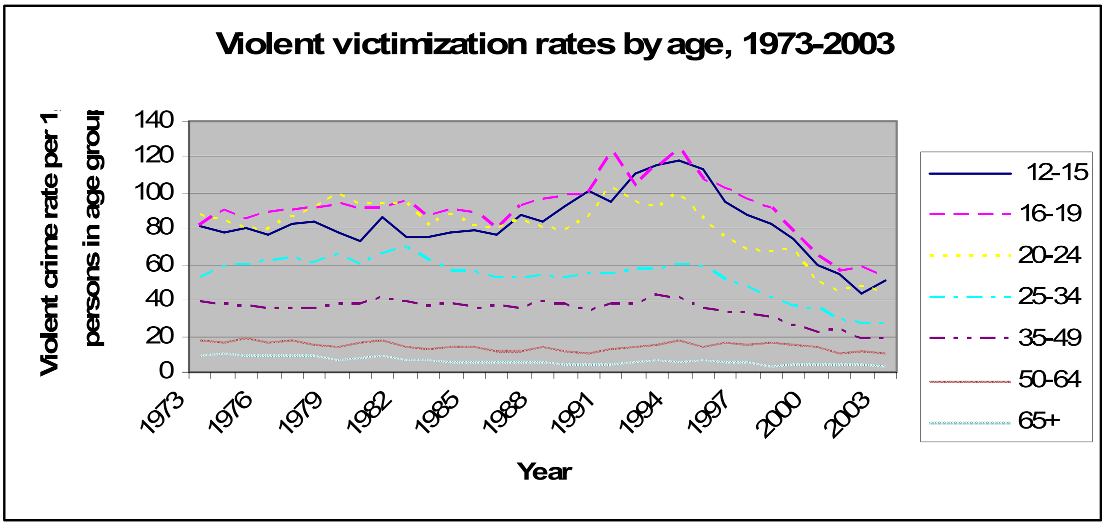
Bureau of Justice Statistics
http://www.ojp.usdoj.gov/bjs/glance/tables/viortrdtab.htm

Appendix II: Property Crime Victimization Rates



Bureau of Justice Statistics
http://www.ojp.usdoj.gov/bjs/glance/tables/proptrdtab.htm

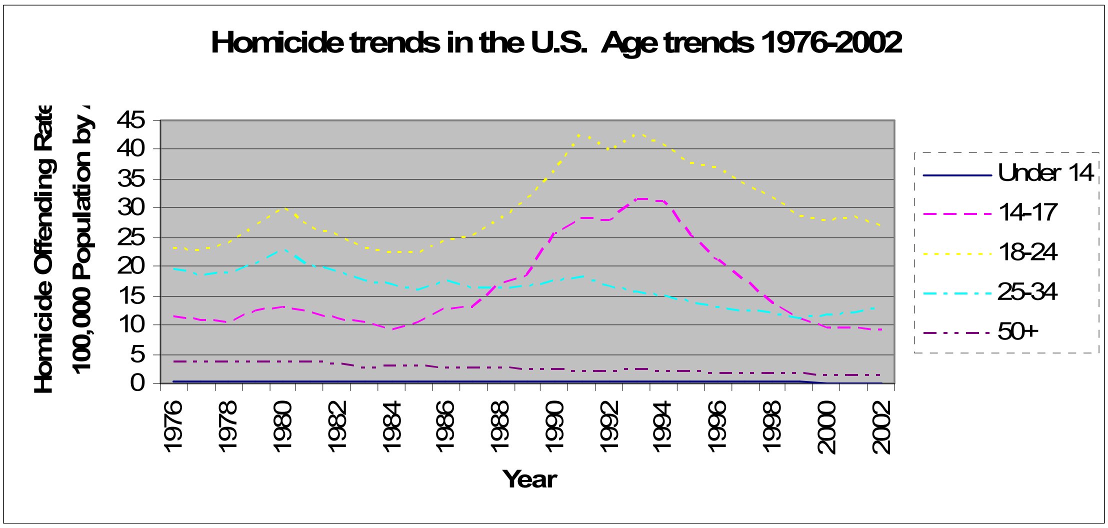
Appendix III: Violent Victimization Rates by Age



Bureau of Justice
<http://www.ojp.usdoj.gov/bjs/glance/tables/vagetab.htm>

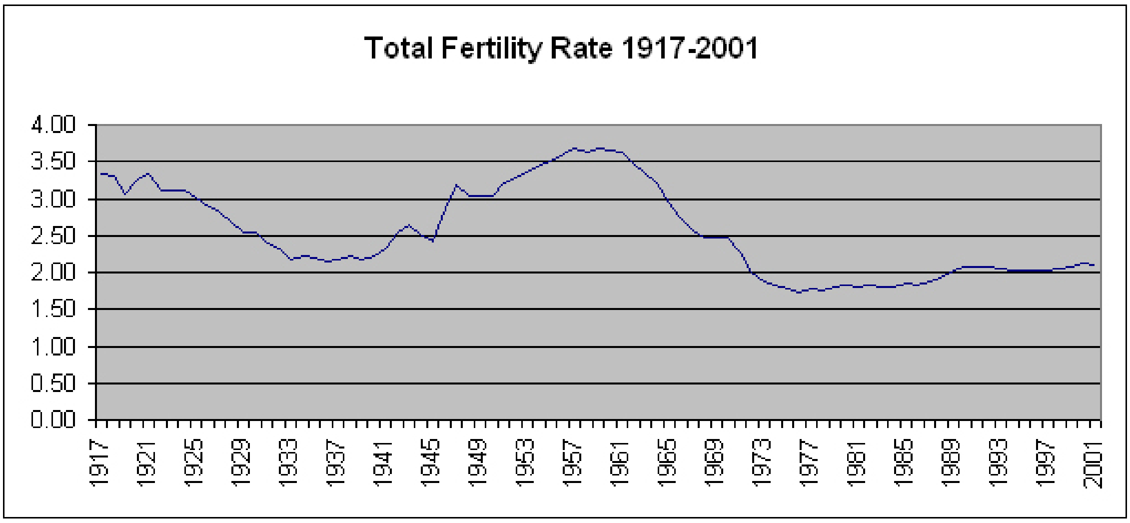
Appendix IV.

Homicide Trends in the U.S.



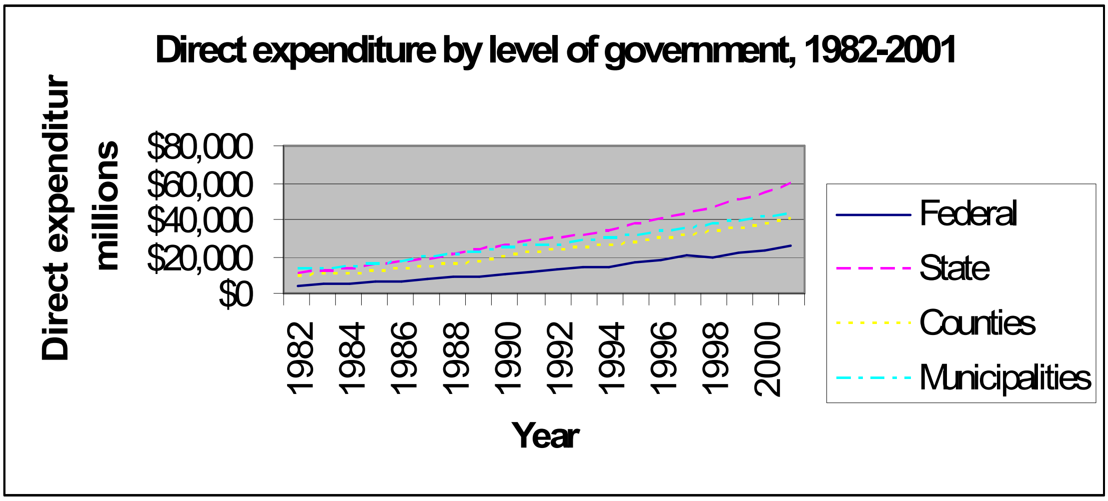
Bureau of Justice
<http://www.ojp.usdoj.gov/bjs/glance/tables/homagetab.htm>

Appendix V: Historical Total Fertility Rate



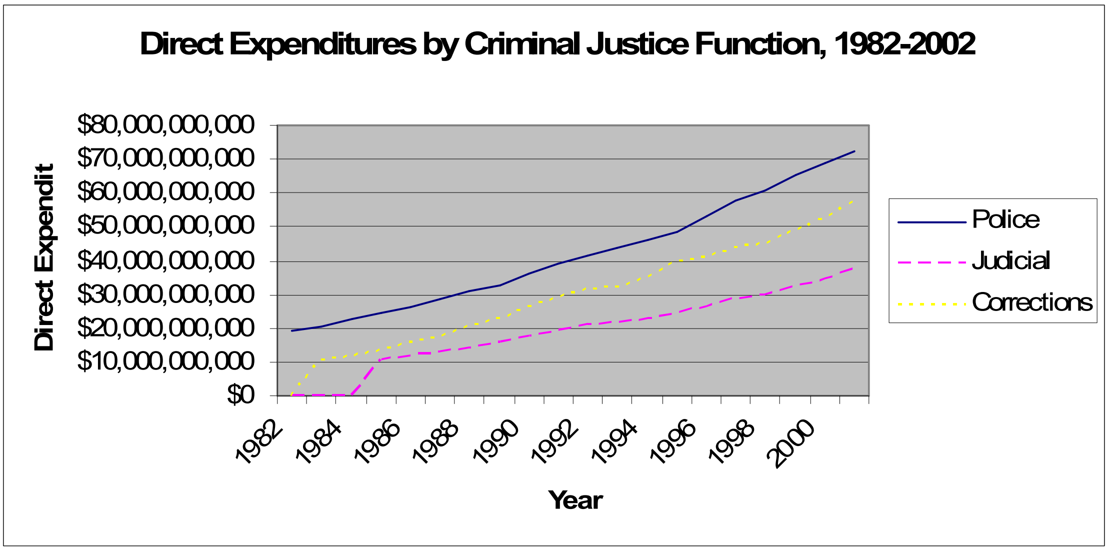
Sources:
Hauser, Robert. Fertility Tables for Birth Cohorts by Color: United States 1901-1973. (Rockville, MD: National Center for Health Statistics, 1976).
National Center for Health Statistics, Vital Statistics of the United States, 1969, Volume I, Fatality (Rockville, MD: U.S. Department of Health and Human Services, 1974.
National Center for Health Statistics, "Births: Final Data"
Population Reference Bureau < http://www.prb.org/pdf/USFertilityTrends2.pdf>

Appendix VI.: Direct Expenditure by Level of Government



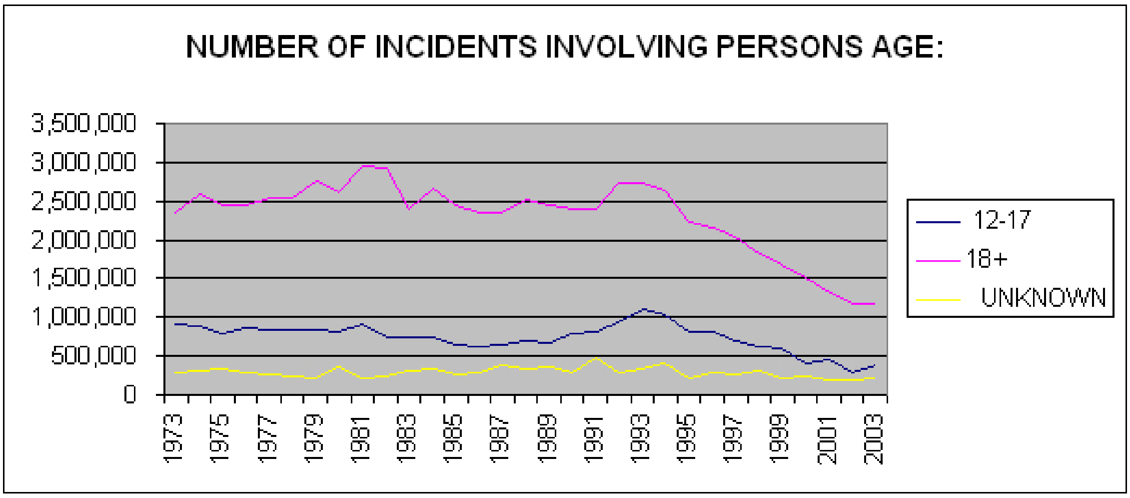
Bureau of Justice Statistics
<http://www.ojp.usdoj.gov/bjs/glance/tables/expgovtab.htm>

Appendix VII:
Direct expenditures by criminal justice function



Bureau of Justice Statistics
<http://www.ojp.usdoj.gov/bjs/glance/tables/exptyptab.htm>

Appendix VIII: Victim's perception of the age of the offender in serious violent crime



Bureau of Justice
<http://www.ojp.usdoj.gov/bjs/glance/tables/offagetab.htm>

Appendix IX: A Case between Friends

		A		B
0	$.8 \le \alpha AA,t \le 1$	1.500	$0.8 \le \alpha B,B,t \le .1$	0.825
1	0.893	1.428	0.877	0.908
2	0.883	1.367	0.913	0.953
3	0.845	1.303	0.915	0.989
4	0.911	1.275	0.997	0.989
5	0.911	1.249	0.946	1.005
6	0.855	1.214	0.823	1.048
7	0.886	1.195	0.977	1.052
8	0.817	1.169	0.996	1.052
9	0.801	1.146	0.886	1.066
10	0.856	1.134	0.900	1.073
11	0.954	1.131	0.926	1.078
12	0.932	1.128	0.984	1.079
13	0.906	1.123	0.904	1.084
14	0.980	1.122	0.872	1.089
15	0.911	1.119	0.849	1.094
16	0.935	1.118	0.981	1.094
17	0.886	1.115	0.974	1.095
18	0.840	1.112	0.996	1.095
19	0.835	1.109	0.907	1.096
20	0.948	1.108	0.800	1.099

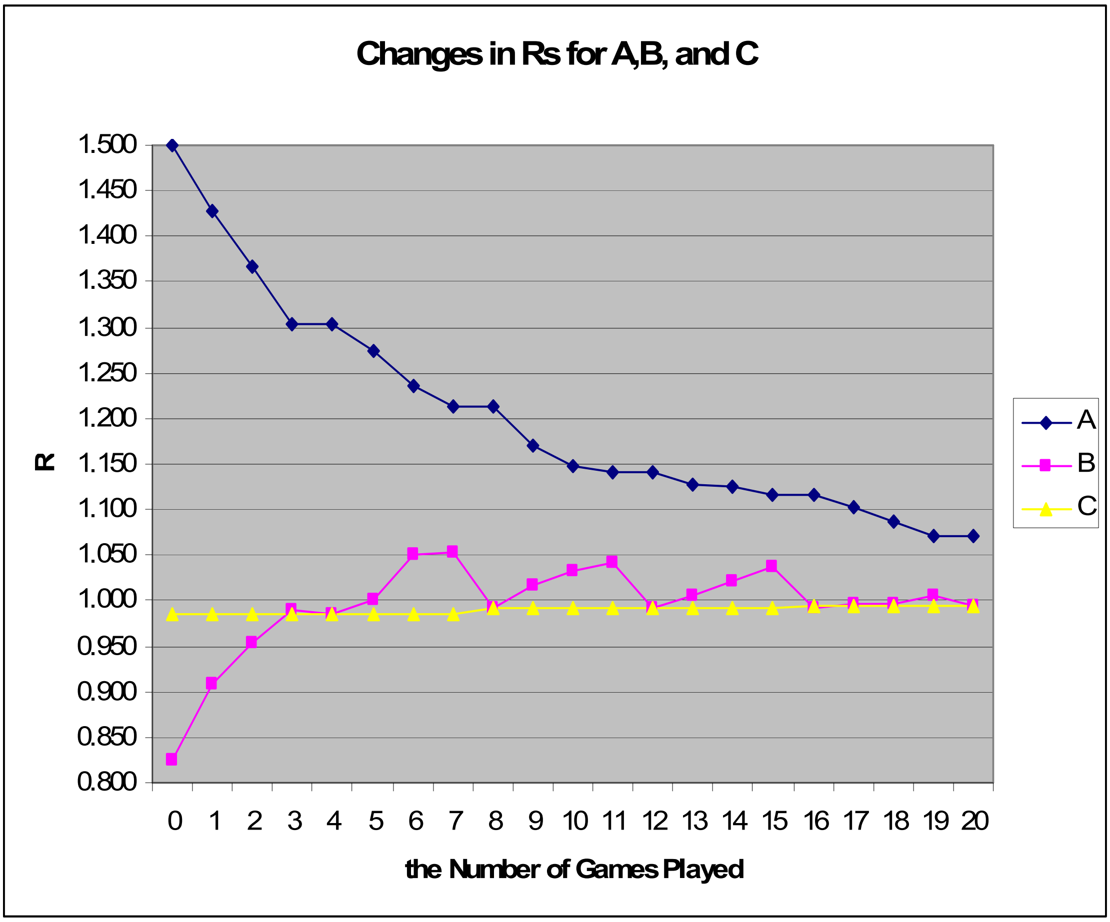
Appendix X: A Case between a Parent and Child

		C		B
0	$.9 \le \alpha C,C,t \le 1$	0.985	$0 \le \alpha B,B,t \le .2$	0.825
1	0.996	0.984	0.184	0.956
2	0.987	0.984	0.008	0.984
3	0.992	0.984	0.041	0.984
4	0.960	0.984	0.009	0.984
5	0.921	0.984	0.061	0.984
6	0.943	0.984	0.068	0.984
7	0.900	0.984	0.177	0.984
8	0.903	0.984	0.101	0.984
9	0.982	0.984	0.150	0.984
10	0.993	0.984	0.112	0.984
11	0.948	0.984	0.078	0.984
12	0.987	0.984	0.001	0.984
13	0.909	0.984	0.134	0.984
14	0.917	0.984	0.027	0.984
15	0.927	0.984	0.180	0.984
16	0.972	0.984	0.014	0.984
17	0.934	0.984	0.165	0.984
18	0.934	0.984	0.048	0.984
19	0.903	0.984	0.199	0.984
20	0.960	0.984	0.020	0.984

Appendix XI: A Case among A, B, and C

		A vs. B		B vs. A		C vs. B		B vs. C
0	$.8 \leq \alpha A,A,t \leq 1$	1.500	$0.8 \leq \alpha B,B,t \leq .1$	0.825	$.9 \leq \alpha C,C,t \leq 1$	0.985	$0 \leq \alpha B,B,t \leq .2$	0.825
1	0.893	1.428	0.877	0.908		0.985		0.908
2	0.883	1.367	0.913	0.953		0.985		0.953
3	0.845	1.303	0.915	0.989		0.985		0.989
4		1.303		0.985	0.960	0.985	0.009	0.985
5	0.911	1.274	0.946	1.002		0.985		1.002
6	0.855	1.235	0.823	1.050		0.985		1.050
7	0.886	1.214	0.977	1.054		0.985		1.054
8		1.214		0.992	0.903	0.992	0.101	0.992
9	0.801	1.170	0.886	1.017		0.992		1.017
10	0.856	1.148	0.900	1.033		0.992		1.033
11	0.954	1.142	0.926	1.041		0.992		1.041
12		1.142		0.992	0.987	0.992	0.001	0.992
13	0.906	1.128	0.904	1.006		0.992		1.006
14	0.980	1.126	0.872	1.022		0.992		1.022
15	0.911	1.117	0.849	1.038		0.992		1.038
16		1.117		0.993	0.972	0.994	0.014	0.993
17	0.886	1.103	0.974	0.996		0.994		0.996
18	0.840	1.086	0.996	0.997		0.994		0.997
19	0.835	1.071	0.907	1.005		0.994		1.005
20	0.948	1.071	0.800	0.994	0.960	0.994	0.020	0.994

Appendix XII: The Graph for Rs in CASE III



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