The Dynamics of Street Gang Growth and Policy Response

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1. THE DYNAMICS OF STREET GANG GROWTH

Street gangs have emerged as tremendously powerful institutions in many communities. In urban ghettos, they may very well be the most important institutions in the lives of a large proportion of adolescent and young adult males. In this paper, we will examine the dynamics of street gang growth and the effects of efforts to control it. Our most basic hypothesis is that there is an intrinsic dynamic that drives the growth of street gangs. Thus, the growth of the gang population is a function of its size.

The most important reason why size and growth rate are related is probably that gang participation is contagious. Ethnographic work emphasizes the importance of peer influence and social bonding both in the initial decision to join a gang and in the maintenance of membership, often through a lengthy prison term (e.g., Cohen, 1955; Crane, 1989; Hagedorn, 1988; Padilla, 1992; Moore, 1978, 1991; Short and Strodtbeck, 1965; Taylor, 1990). Empirical tests of differential association theory, while not addressing the issue of gang participation per se, have consistently
demonstrated that associating with peers who engage in delinquent acts is one of the most (and perhaps the most) important determinants of delinquent behavior and drug use (Elliot et al., 1979, 1985; Ginsberg and Greenberg, 1978; Glaser, 1960; Kandel, 1974; Krohn, 1974; Krohn et al. 1984; Johnson et al., 1987; Matsueda, 1982; Matsueda and Heimer, 1987; Reinerman and Fagan, 1988; and see Matsueda, 1988, for a review). The fact that social learning is an intermediate step in the contagious process suggests that the correlations among the behaviors of friends is not merely a product of homophily, the tendency of people to seek out associates like themselves (see Johnson et al., 1987; Krohn et al., 1984; Matsueda, 1982; Matsueda and Heimer, 1987).

It is primarily the dynamics of the contagious process that makes the growth rate of gangs a function of their size. Each gang member is also a potential “carrier.” Each new member expands the network of relationships between gang members and nonmembers. More contacts are likely to yield more recruits, at least up to a point.

But direct peer influence is not the only thing that contributes to the relationship between size and growth rate. There are at least five other factors. First, as gang membership rises to some substantial proportion of a cohort in a community, subcultural norms may evolve that give status to gang membership (Anderson, 1990; Cohen, 1955; Hannerz, 1969; Matza, 1964; Padilla, 1992; Short and Strodtbeck, 1965). Second, there are economies of scale associated with the development of market infrastructure (Crane, 1990; Fusfield and Bates, 1984; Martinez, 1992; Padilla, 1992). The emergence of a large gang in a community may help establish a black market in drugs or other illicit goods and services. If this occurs, profits and wages in illegitimate enterprises may rise sharply, attracting entrepreneurs and workers. If gangs control the market, gang membership may be a prerequisite for gaining access to it.

Third, the increase in crime associated with a rise in gang activity may push legitimate businesses out of inner city communities, exacerbating a trend generated by structural changes in the economy. When opportunities to make money and attain status in legal jobs disappear, illegitimate opportunities become relatively more attractive (Hagan, 1991; Hagedorn, 1988; Moore, 1991; Williams, 1989; Wilson, 1987). Fourth, the growth of one gang may

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Note that the hypothesis of self-generated growth is not inconsistent with structural theories of gang involvement that emphasize economic opportunities and status rewards. Structural factors could be exogenous causes of gang participation in a self-generated growth model. They could even be the primary ones, as long as one or more self-generating processes play an intermediate role in the growth dynamics of the gang population.
generate the creation of other gangs as people bond together to protect themselves (Martinez, 1992; Padilla, 1992). And fifth, as rivalries between gangs grow, gangs often make organized efforts to recruit and even coerce people into joining. This is because size confers an advantage in fights over territory and/or market share (Crane, 1989; Padilla, 1992).

Of course, this self-generated growth will not continue forever. Ultimately, each factor becomes self-limiting or reaches a maximum. As the exposure to peer influence approaches 100 percent of the community, the rate of new exposure must begin to slow down at some point. The status associated with joining a gang reaches a maximum eventually. Once the black market is established, economies of scale may no longer operate. As the number of legitimate businesses in the community approaches zero, job loss must slow down. Gang wars may make membership riskier than nonmembership. And in every community, there are some individuals who will never join a gang no matter how much they are threatened or coerced.

In addition to being self-limiting, other social forces may also limit the growth process. As gang membership grows, community uproar may galvanize public action. As more public resources are devoted to the gang problem, the social and economic costs of gang membership rise. The chances of being arrested increase. Profits and wages in the black market fall.

In this paper, we develop a model of how the size of the street gang population in a community is determined. The two key factors that determine the population’s size are: (1) the intrinsic growth trajectory that defines a functional relationship between the level of the population and its growth rate; and (2) the magnitude of the public response to the level of the population. It turns out that this model has important implications for public policies aimed at reducing gang populations. But before detailing the model, we will first consider its place in the context of the relevant literature.

2. PREVIOUS MODELS IN THE LITERATURE

Historically, research on gangs per se, has been ethnographic or empirical in nature. There is no tradition of formal theory on gang behavior. However, in recent years there has been a spate of papers presenting formal models of related phenomena, such as underclass behavior, delinquency, and other social problems. Although these models are very different from each other in most
ways, they share a common element. They are all predicated to some degree on some sort of contagious process.

Rowe and others developed a class of models which they call, “epidemic models of the onset of social activities.” They used them to model such adolescent social problems as sexuality, smoking, drinking, delinquency, and crime (Rogers and Rowe, 1993; Rowe and Gulley, 1992; Rowe et al., 1989, 1992a, 1992b; Rowe and Rodgers, 1991a, 1991b). These models classify individuals into a discrete number of states that are defined with respect to the intensity of their involvement with or susceptibility to developing some socially problematic behavior. They are essentially Markov models. There is a certain probability that contact between individuals in different states will lead to transitions from one state to another. The states are different in each specific model.

Crane (1989) used a somewhat similar mathematical model to develop a theory of how urban neighborhoods evolve into ghettos with rampant social problems. He argued that social problems are contagious, particularly among adolescents, because of peer influence. The model assumes that individuals will develop a social problem when a particular proportion of their peers do.

Montgomery (1990, 1991) developed a rational choice model of “underclass behavior.” Drawing on preference theory from economics, he specified various choice problems in which individuals pick between underclass and main-stream behavior to maximize their utility. He built contagion effects into the model by hypothesizing that the utility of underclass behaviors increases as the proportion of people in the community choosing underclass behavior rises, because people confer approval and social status upon people who adopt their subcultures.

Martinez-Vazquez and Saposnik (1990) did a dynamic analysis using a model similar to that of Montgomery’s (which they developed independently). In their model, there are two mechanisms of the contagion effect. In addition to a status effect like the one posited by Montgomery, there is an income effect. They assumed that the presence of more members of the underclass in a neighborhood creates better opportunities for making money in illegal ways. They used this model to trace the growth of the underclass population over time under various distributional assumptions.

Wallace (1988, 1989, 1990, 1991) modeled a different type of contagion to describe recent patterns of urban decay in ghettos. He hypothesized that increases in the incidence of one type of social problem can lead to increases in the incidence of others,
because of various types of economic externalities and social spill-over effects. He used systems of partial differential equations to model interactions between rates of violent death, housing abandonment, homelessness, fires, substance abuse, and AIDS.

Empirical testing confirms the validity of these models. Rowe and his colleagues have done the most extensive empirical work. Their Markov models consistently yield reasonably accurate predictions of the incidences of various social problems (Rogers and Rowe, 1993; Rowe and Gulley, 1992; Rowe et al., 1989, 1992a, 1992b; Rowe and Rodgers, 1991a). Crane (1989) found that distributions of the rates of various types of crimes in the neighborhoods of Chicago and Los Angeles were consistent with his model. Crane (1991) found that particular nonlinear patterns of neighborhood effects on dropping out and teenage childbearing were also consistent with that same model; and Wallace (1990) found significant geographic correlations among the rates of different social problems, as predicted by his model.

There is no empirical work on gang populations that would enable us to address the issues raised by these models directly. But Hutson et al. (1995) found that, over the last 16 years, there has been an epidemic of gang-related homicides. This pattern of growth is similar to that of a number of the social problems modeled in the papers described above.

The model developed in this paper is unique in two ways. First, it deals with the problem of gangs specifically, rather than with related phenomena. Second, it is more general than those described above in that it is not explicitly predicated on an assumption of contagion. Nevertheless, it is completely consistent with such an assumption, and given the literature reviewed above, we believe that contagion probably is an important factor in the gang growth process.

3. THE MODEL

On a very general level, the relationship between gang population growth and the social control response can be represented by the classic predator–prey model in ecology (Lotka, 1925; Volterra, 1925). This model assumes that two factors determine the prey population, in this case the number of gang members in a community. One is the natural growth trajectory of the prey in the absence of the predator, which defines the relationship between the size of the population and the growth rate. The other is the magnitude
of the response of the predator to the level of the population. In this case, the “predator” takes the form of public programs aimed at reducing the size of the gang population either by rehabilitating or incarcerating gang members. The only other assumption of the general model is that the relationship between the two factors is additive, which is simplest and seems to be accurate for predator–prey relationships in nature. More formally, we will assume that the growth rate of the gang population is given by (1):

$$\frac{dx}{dt} = g(x) - p(x)$$  \hspace{1cm} (1)

where $x$ is the size of the gang population at time $t$, $g(x)$ is the intrinsic growth function, and $p(x)$ is the public response function that describes the amount of resources the public devotes to the problem at each level of the population.

To glean some insights into the dynamics of the gang population, we must specify functional forms for $g(x)$ and $p(x)$. As discussed above, there are several reasons why the growth rate of gangs will tend to increase with the size of the population and then level off at some point. This is an extremely common pattern for many different types of populations. It can be modeled in a very general way with the logistic function (Pearl and Reed, 1920; Verhulst, 1838). We will use a slight variant of this function (by adding an initial condition). Suppose that, in the absence of exogenous forces (i.e., $p(x) = 0$), the growth of gang membership over time can be described in this way (2):

$$\frac{dx}{dt} = g(x) = r(x + x_0)(1 - x/k)$$  \hspace{1cm} (2)

where $r$, $k$, and $x_0$ (the initial condition\(^2\)) are positive constants.

Figure 1a shows how the growth rate varies with the size of the gang population, and Figure 1b shows the time path of the population. The gang grows first at an increasing rate to some point. Then the rate of growth levels off, and the population approaches some maximum level $k$ asymptotically, as $t$ approaches infinity.

For the response function, assume that as gang membership in a community grows, the public will devote more resources to the problem. So $p(x)$ is monotone increasing. But because resources are limited, the investment will ultimately reach or approach some

\(^2\text{Note that the initial condition implies that a gang population of zero is not an equilibrium, since at } t = 0 \text{ and } x = 0, \frac{dx}{dt} = rX_0. \text{ If the initial condition is omitted, the details of the analysis are a little different, but the basic results are the same.}
maximum level. This pattern of response can be modeled in a very general way, as follows (3):

\[ p(x) = ax^\alpha/(b + x^\alpha) \]  

(3)

where \( a, b, \) and \( \alpha \) are each constants greater than 0. Note that \( p(x) \) approaches a asymptotically as \( x \) approaches infinity, so \( a \) is the maximum response level. The parameters \( b \) and \( \alpha \) are inversely related to \( p(x) \). Thus, if \( b \) and/or \( \alpha \) are relatively small, \( p(x) \) approaches the maximum relatively quickly as \( x \) rises (i.e., the public responds more aggressively to a growing gang population).
4. ANALYSIS

For convenience, scale the units in the following way (4,5):

\[ X = x/k \quad X \text{ varies from } 0 \text{ to } 1 \quad (4) \]

\[ T = rt \quad (5) \]

In other words, \(1/r\) is the unit of time. And \(X\) is the proportion of the population in the gang. This implies (6–8):

\[ \frac{dX}{dT} = F(X) = (X + X_0)1 - X - AX^a(B + X^a) \quad (6) \]

where

\[ A = a/rk \quad (7) \]

and

\[ B = b/k^a \quad (8) \]

Note that \(A\) and \(B\) are simply scaled versions of the parameters \(a\) and \(b\).

At equilibrium, \(F(X) = 0\). In the neighborhood the equilibrium point \(X^*\) (9):

\[ F(X) = F(X^*) + F'(X^*)(X - X^*) + \ldots \quad (9) \]

Define \(\mu = X - X^*\) and \(\lambda = F'(X^*)\). Then the time path close to equilibrium can be described by the linear differential equation (10,11):

\[ \frac{d\mu}{dT} = \lambda \mu \quad (10) \]

with the solution

\[ \mu = \mu_0 e^{\lambda T} \quad (11) \]

An equilibrium is stable if \(\lambda < 0\) and unstable if \(\lambda > 0\). There will be either one or three equilibria. Figure 2a, 2b, and 2c shows the shape of \(F(X)\) and the equilibria in three possible cases (i.e., for different values of \(A\) and \(B\)). In Figure 2a, there is one stable equilibrium at some relatively low level of gang membership. In Figure 2b, there is one stable equilibrium at a relatively high level. In Figure 2c, there are three equilibria. The one in the middle is unstable, while the low and the high ones are stable. Beginning from zero, the gang population will wind up at the lowest stable equilibrium.
The case depicted in Figure 2c is important, because it suggests the possibility of epidemics of gang growth. Suppose that the gang population in a community is at the low, stable equilibrium. Then some temporary exogenous shock pushes the population above the unstable equilibrium. Gang membership will rise to the high,
Figure 3. (a) A transition from a low equilibrium to a high one. (b) A transition from a high equilibrium to a low one.

stable equilibrium and stay there, even if the exogenous forces stop operating.

If the shock just happens to make the population rise to the unstable equilibrium exactly, it will stay at that level. But because this middle equilibrium is unstable, any increase in membership, even a very small one, will set the population in motion toward the high equilibrium. Any decrease in membership will cause it to fall back toward the low equilibrium.

An epidemic could also be generated endogenously, i.e., by a change in the shape of $F(X)$. Changes in either the intrinsic growth of the gang or the public response function lead to changes in the equilibria. Jumps in the equilibrium level of gang membership
occur when a point loses its stability. Figure 3a depicts a transition from a low equilibrium to a high one, while Figure 3b shows a transition from high to low.

Note that the two types of transitions may not take place at the same point. This fact is very important. It implies that if some change in the population causes an epidemic, we may not be able to return to the *status quo ante* by changing the characteristics of the population back to the way they were before. For example, suppose that initially the population is at the low equilibrium shown in the Figure 3a. Then the intrinsic growth of the gang rises, and the population increases to the high equilibrium. Even if we then intervened with some policy that succeeded in reducing intrinsic gang growth to its original pattern, the population would remain at a high equilibrium, because it is stable. To return to the low equilibrium, we might have to reduce intrinsic growth well below its original level, which could be far more costly and might not even be possible.

This phenomenon, in which transitions in opposite directions between two states occur at different points, is known in the physical sciences as hysteresis. It is important in this case, because it suggests that the prevention of epidemics of gang growth should be a high priority in making public resource allocation decisions, at least in certain situations. The social and economic costs of allocating too few resources to control gang growth in a community may be high indeed. And, in contexts of uncertainty, the costs of erring on the side of devoting too few resources to the problem may thus be greater than the costs of erring on the side of devoting too many.

To determine the importance of the hysteresis effect, we have to determine the conditions under which it is operative and the magnitude of the difference between the transition points. To do this, it is helpful to determine, for various values of $\alpha$, the domains in $(A,B)$ space where are one or three equilibria. At equilibrium, $dX/dT = 0$, so (12):

\[
(X + X_0)(1 - X) = AX^{\alpha}(B + X^{\alpha})
\]  

This equation has a double root if (13):

\[
\frac{d(X + X_0)(1 - X)}{dX} = \frac{d(AX^{\alpha}(B + X^{\alpha}))}{dX}
\]

Using Equations 12 and 13 to solve for $A$ and $B$, yields (14):
There are two cases, depending upon the value of \( \alpha \). Figures 4 and 5 show the domains of one low, one high, and three equilibria in \((A,B)\) space. Figure 4 shows an example of the case of \( \alpha < \alpha_0 \), while Figures 5 shows an example of the case of \( \alpha > \alpha_0 \). The key difference between the cases is that in the second one there is a cusp,\(^3\) while in the first there is not. As discussed below, this implies that hysteresis is very general phenomenon in the first case but a highly local one in the second.

Recall that \( B \) and \( \alpha \) are inversely related to the strength of the public response at each level of the gang population. The parameter \( \alpha \) is an especially sensitive indicator of the initial growth of the public response. \( A \) is a scaled version of the maximum response level. However, changing \( A \) while holding \( B \) and \( \alpha \) constant will change the whole shape of the function. So changes in \( A \) also affect the strength of the response at finite values of \( X \). In contrast to \( B \) and \( \alpha \), \( A \) is positively related to the size of the response at each level of gang membership.

\(^3\)This result is known generically in mathematics as a “cusp catastrophe.”
In Figures 4 and 5, the horizontal and vertical distances between the two boundaries are measures of the magnitude of the hysteresis phenomenon at a particular level of $B$ (horizontal) or $A$ (vertical). For example, suppose that gang membership is at a point in the three equilibria domain. Then the amount of public resources devoted to controlling gangs is reduced, i.e., $A$ decreases. When the boundary between the high/three equilibria domains is crossed from right to left, gang membership jumps to a high equilibrium. Suppose then that after this epidemic occurs, the public policymakers realize that they made a mistake and begin to increase $A$. When the high/three boundary is crossed going from left to right, the gang population will remain at a high equilibrium. It will only fall to a low one when the low/three boundary is crossed from left to right.

Thus, if the horizontal distance between the boundaries is large, it means that if an epidemic occurs, reversing it may require that $A$ may have to be raised well beyond its original level. But if the horizontal distance between the boundaries is small, the difference in the values of $A$ for a jump from high to low and a jump from low to high is not very large. All of this also holds true in an analogous way for changes in $B$ at a particular value of $A$. So the vertical distance between the boundaries is another measure of the magnitude of the hysteresis phenomenon at each value of $A$.

Figure 4 shows the boundaries between the three domains for $\alpha < \alpha_0$. In this case, the horizontal distance between the boundaries increases as $B$ increases. Thus the potential for hysteresis, due to
changes in $A$, is greater when $B$ is larger. In other words, as the sensitivity of public response to a rising gang population decreases (at a given value of $\alpha$), multiple equilibria occur over larger ranges of $A$. This implies that increasing the public response could generate greater benefits in situations where the policymakers are responding to gang growth relatively weakly.

Figure 4 also demonstrates that in this range of $\alpha$, the vertical distance between the boundaries increases as $A$ increases. Thus, the potential for hysteresis, due to changes in $B$, is greater when $A$ is larger. And below a certain point, hysteresis cannot occur, because there is no possibility of a single, low equilibrium at such low values of $A$.

Figure 5 shows that in this case, the horizontal distance between the boundaries increases as $B$ decreases, the opposite of the first case. Thus, the potential for hysteresis, due to changes in $A$, is greatest when $B$ is low (but positive). In other words, as the sensitivity of public response to a rising gang population increases, multiple equilibria occur over larger ranges of $A$. This is because as $B$ falls, the level of $A$ needed to assure one equilibrium decreases more slowly than the level needed to generate multiple equilibria. This implies that in this second case, strengthening the public response is more important when policymakers are already responding to gang growth aggressively. Note also that above a certain value of $B$, there is no possibility of hysteresis at all, because the domain of multiple equilibria disappears.

Figure 5 also demonstrates that in this range of $\alpha$, the vertical distance between the boundaries increases as $A$ decreases, to a certain point. But below that point, hysteresis cannot occur, because there is no possibility of a single, low equilibrium at such low values of $A$. So the potential for hysteresis, due to variation in $B$, is greatest when the maximum response level is in some middle range.

Figure 6 demonstrates how the potential for hysteresis changes with variation in $\alpha$. The most striking result is that the domain in which hysteresis can occur expands dramatically as $\alpha$ falls below $\alpha_0$. Decreases in $\alpha$ tend to increase the size of the domain in which hysteresis can occur. Below that point, the boundaries extend to infinity. So the potential for hysteresis exists at all values of $A$ and $B$. But above $\alpha_0$, hysteresis is a much more localized. As noted above, the domain of multiple equilibria and, thus, the possibility of hysteresis, disappears beyond the cusp. Also, hysteresis cannot occur for values of $A$ that are too low. The case of $\alpha = \alpha_0$ is
Figure 6. The shape of the domains at different values of $\alpha$ in relation to $\alpha_0$. 
special. At that point, the domain of multiple equilibrium is a line. So while, technically, hysteresis can occur, the magnitude of the effect is infinitely small.

5. AN EXAMPLE

Suppose that we are concerned about gang activity in a population of 1250 male adolescents (roughly the number in a large urban public high school). Assume that within this population, there are 250 individuals who would never join a gang under any circumstances. Thus, there are 1000 potential gang members ($k = 1000$). Define the unit of time as one month ($r = 1$). Assume that at time 0, gang membership is 0 but the slope is 50. In other words, 50 teens a year are joining the gang. This implies $X_0 = 50/1000 = 0.05$.

What we are interested in is how the gang population varies with the level of public resources. Recall that the level of resources is defined by the parameters $a$, $\alpha$, and $b$. The parameter $a$ determines the basic level, while $\alpha$ and $b$ determine the functional form and slope of the public response to changes in gang membership. For this example, assume that $a = 0.2$ and $B = 0.2$.

Given these parameter values, if $A = a/rk \geq 0.344$, there is one low stable equilibrium. If $A \leq 0.088$, there is one high stable equilibrium. If $A$ falls between these two values there are two stable equilibria.

The parameter of interest is $a$. Its dimensions are dollars budgeted per year to reduce gang membership. Assume that it costs $1,000 to remove one individual from the gang. This could represent resources devoted to any number of uses, such as a delinquency prevention program, policing, adjudication, imprisonment, etc.

In this particular case, there are two stable equilibria if the budget is between $88,000$ and $344,000$ per year. Thus, if the system begins with gang membership at a low stable equilibrium, it could be maintained by as little as $88,000/year. But if the budget falls below $88,000 (or if an exogenous shock generated an epidemic), gang membership would rise to a high stable equilibrium. In that case it would take at least $344,000 to push membership back down to a low equilibrium. Thus, the size of the hysteresis effect in this example is $256,000$. Under these circumstances, the potential benefits of prevention would be very large indeed.

Table 1 shows how the size of the hysteresis effect varies with $a$ and $B$. For the case of $a = 0.2$, the hysteresis effect is very large at $B = 0.2$, and it grows as $B$ increases. For the case of $a = 2$,
Table 1: The Annual Budget Needed to Maintain a Low Equilibrium, and the Number Needed to Change a High Equilibrium into a Low One, for Various Values of $a$ and $B$ ($K = 1.000; X_0 = 0.05$)

<table>
<thead>
<tr>
<th>$B$</th>
<th>Maintain</th>
<th>Change</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case of $a = 0.2$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.2</td>
<td>$88,000</td>
<td>$344,000</td>
<td>$256,000</td>
</tr>
<tr>
<td>0.4</td>
<td>$120,000</td>
<td>$408,000</td>
<td>$288,000</td>
</tr>
<tr>
<td>0.6</td>
<td>$148,000</td>
<td>$476,000</td>
<td>$328,000</td>
</tr>
<tr>
<td>0.8</td>
<td>$180,000</td>
<td>$536,000</td>
<td>$356,000</td>
</tr>
<tr>
<td>1.0</td>
<td>$208,000</td>
<td>$600,000</td>
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<tr>
<td>0.002</td>
<td>$156,000</td>
<td>$276,000</td>
<td>$120,000</td>
</tr>
<tr>
<td>0.004</td>
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<td>$280,000</td>
<td>$92,000</td>
</tr>
<tr>
<td>0.006</td>
<td>$212,000</td>
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<tr>
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<td>$284,000</td>
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<tr>
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<td>$308,000</td>
<td>$0</td>
</tr>
</tbody>
</table>

The hysteresis effect is quite large for values of $B$ greater than or equal to 0.01. But the effect shrinks at $B$ rises, and at values of $B = 0.024$ and above, hysteresis does not occur.

6. DISCUSSION

Recall that epidemics of gang growth can be generated either exogenously or endogenously. An exogenously generated epidemic is one in which the population jumps from a low, stable equilibrium up above an unstable equilibrium and then gradually moves toward a high, stable equilibrium, even though $F(X)$ does not change. An endogenously generated epidemic is one in which a change in $F(X)$ causes the population to move from a low, stable equilibrium to a high, stable equilibrium. Each type has some implications for public policy, especially resource allocation decisions.

The exogenous case represents the effects of anything besides a change in either the intrinsic growth trajectory of the gang or the public response. Some examples of phenomena that might cause a rise in intrinsic growth are: a fall in youth employment (perhaps due to a national recession or the closing of a large local employer); a substantial increase in the profitability of drugs (such
as that which occurred with the introduction of crack cocaine in the mid-1980s; or perhaps even a trend toward the romanticization of gang activity in popular culture (which may be occurring now in rap music and movies). When dramatic increases in gang populations have occurred, local and state governments, and occasionally even the federal government, have attempted to intervene to reverse the rise. Youth employment programs, educational programs in schools, and advertising campaigns are some of the more common interventions that have been tried (in addition to increases in public resources, which are discussed below). There is some evidence that such interventions can prevent some individuals from joining a gang, at least in the short run. But none of them seem to have had much of effect on overall gang populations. Our model suggests one possible reason for this.

As Figure 2c above shows, small-scale interventions to reduce gang activity may have no permanent effect at all. An intervention may temporarily push gang membership below its equilibrium. But unless the intervention is large enough to push the population all the way down to the unstable equilibrium, membership will move back up to the high equilibrium.

Although this implication is pessimistic, the model does suggest a resource allocation strategy that could succeed. If an intervention is large enough to push gang membership just below the unstable equilibrium, the population will revert to the pre-epidemic low equilibrium and stay there of its own accord. Because of the stability of the low equilibrium, the intervention does not have to be continued once the low level is achieved. Thus, a short-term but high-intensity intervention might succeed where a long-term, low-intensity strategy would fail.

If this model is an accurate characterization of the dynamics of gang development in the neighborhoods of American cities, it suggests a broad resource allocation strategy for dealing with the problem. Spreading resources too thin by addressing the problem in all or many communities at once would result in universal failure. A strategy of “sequential saturation” would be more effective. This would involve saturating one or a few communities at a time to reduce the gang population enough that it would begin moving by itself toward a low, stable equilibrium. Once that was achieved, the resources could then be moved to a different community, because the stable equilibrium would act as an anchor, preventing long-run increases in the absence of another exogenous
shock large enough to push membership up past the unstable equilibrium.

The model also suggests that we might want to identify communities that seem at imminent risk of an epidemic of gang growth and establish prevention programs in them. Preventing exogenously generated epidemics can be much cheaper than reversing them, because a low, stable equilibrium acts as a natural anchoring force.

Prevention can also be much cheaper than cure for endogenously generated epidemics as well. An epidemic of gang growth could be generated endogenously in one of two basic ways. One way would be if the policymakers changed their resource allocation policies and, thus, their response strategy. Reducing the overall commitment of resources at each level of the gang population is the most obvious change that could engender an epidemic. But it is not the only one. Changes in the timing of the public response could also have an effect. In particular, reducing the response to growth at low levels of the population could cause an epidemic that could not be stopped even if the subtraction of resources is more than made up for later.

This is not an unrealistic scenario. Policymakers dealing with a gang problem have to allocate resources among different communities. It is easy to imagine a situation in which resources are moved from one community with a minor gang problem to another community with a major problem. Then an epidemic occurs in the first community. Stung by the mistake, the policymaker reverses course and moves back into the first community with more resources than it would usually commit to controlling even the new, high level of gang activity. But it is too late, because the epidemic level of the population is being anchored by a high, stable equilibrium.

The second way an epidemic could be generated endogenously would be if there was a permanent change in the intrinsic growth trajectory of the gang population. This could happen for many reasons. One real-life example is particularly illustrative. According to widespread media reports, the Bloods and the Crips, two Los Angeles gangs, made a concerted effort to expand into medium-sized cities in the West and Midwest, in the late 1980s. They set up drug gangs and invested in black-market infrastructure. This process of institution building caused the gang population in these cities to rise. The changes seem to be permanent, since gang activity has remained high ever since.

The analysis of endogenously generated epidemics above suggests that in some circumstances, trying to prevent epidemics of
gang growth by allocating public resources in particular ways can be very cost effective. In such situations, the policymakers should be hesitant to move resources out of a quiescent area, lest an epidemic occur. And they should try to identify communities at risk of an epidemic, and then move more resources there. But in other circumstances, hysteresis cannot occur, or the effects would be small if it did. In those cases, responding after an increase in the gang population occurs is not more costly than preventing the rise in the first place (given those factors considered in our model). So policymakers can base their resource allocation decisions solely on what has happened, rather than also taking into account what might happen.

What are the circumstances under which prevention is beneficial? Prevention should be a relatively higher priority when potential hysteresis effects are more likely and/or larger. The specific conditions under which this is true are detailed in the analysis above. They are somewhat involved and hard to describe specifically without using mathematics. But one general principle does emerge from the analysis. Prevention has greater potential benefits if the public can respond quickly to growth in the gang population at low levels. Given reasonable budget constraints, this may not be possible in all communities at once. But a few communities with the highest risks of suffering an epidemic of gang growth could be targeted. In those communities, policymakers could respond as soon as growth in gang activity was observed. And extra resources could be kept there even if the growth was stopped, to prevent a possible epidemic in the future.

The basic model presented here is so general that the possibility of hysteresis under some range of parameter values is virtually universal. It exists even without the simple additivity assumption embedded in Equation 1. However, the precise range of parameter values under which hysteresis actually occurs, as well as the size of the effect (and, thus, its importance to policy), varies with functional form and the values of the exogenous parameters. Therefore, it would always be necessary to do sensitivity analyses of the type presented in Figure 6 to determine whether the kinds of policies suggested above would actually be cost effective in specific situations.

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4 There may be, and in fact probably are, other reasons why prevention is cost effective. For example, it is probably harder and costlier to persuade an individual to leave a gang than to prevent him from joining one in the first place. But this “psychological hysteresis” is not the same as the hysteresis discussed in the model, which is a product of the dynamics of the social process.
7. CONCLUSION

Our model of the size of the gang population generates multiple equilibria under particular conditions. This suggests the possibility of large jumps in the size of the gang population, i.e., epidemics of gang growth. These epidemics could be generated by factors exogenous to the model, such as a change in the social, economic, or cultural conditions that cause people to join gangs. Or they could be generated by factors endogenous to the model, a change in the intrinsic growth trajectory of the gang or in the allocation of public resources. Further analysis reveals that endogenously generated epidemics may be characterized by hysteresis under certain circumstances. The possibility of epidemics and hysteresis suggests some general strategies for the prevention and reversal of gang growth. Analysis of the mathematical conditions under which these phenomena occur yields specific conditions under which these would be most beneficial.

Could these results be useful to policymakers in the real world? Could the functions and values necessary to specify the model actually be estimated? As noted in Section 3 above, empirical analysis suggests that similar models yield fairly accurate predictions about the incidence and growth rates of related phenomena. So it is not completely implausible that a policymaker might be able to use the model presented here (or one similar to it) to estimate a precise allocation.

But even if these models could not be specified and estimated, the general insights generated in the analysis of the model would still useful to policymakers as a guide for developing general strategies. In communities at risk, we would want to set up social and economic interventions to prevent exogenously generated epidemics. To prevent endogenously generated epidemics, we would want to invest extra resources aimed at controlling gangs even in the absence of any growth there. And we would want the policymakers to respond quickly and strongly to gang growth at low levels.

In communities that had already suffered epidemics, we would want to try a strategy of sequential saturation to reverse exogenously generated epidemics. Rather than spreading resources thin across all of them, we would want to concentrate resources in one or a few of them at a time. If it turned out that the epidemic was reversed by saturating the community with interventions, we could
then move the bulk of the resources to another community suffering an epidemic (leaving behind a fraction of the resources that would be aimed at preventing an epidemic from reoccurring in what would presumably now be a community at risk).

Could we identify communities at risk and/or communities where epidemics have occurred? Perhaps so. If such high and low equilibria do exist, then the distribution of gang membership in the neighborhoods of American cities should be divided into two separate distributions (or at least two separate modes), a large one in a low range and a small one in a high range. The small distribution (or mode) in the high range of gang population would consist of those communities that had suffered epidemics. Communities at risk would be harder to identify, but there are at least three obvious characteristics to look for: (1) gang populations at the right tail of the low-level distribution; (2) demographic similarity to the communities where epidemics had already occurred; and (3) geographic proximity to communities with epidemic levels of gang membership. Over time, we could test and refine our risk indicators by observing which communities wound up experiencing epidemics.

Carne (1989) found that arrests for juvenile crime in Chicago neighborhoods and murder rates in Los Angeles police districts followed a bi-distributional or bimodal pattern in the 1980s. Particular ghetto and barrio neighborhoods had crime rates so much higher than all other communities that they formed a separate distribution, or at least a separate mode. Although this does not prove the existence of epidemics and stable equilibria, it is exactly the pattern that the model predicts. And while these are not measures of the gang population per se, they are probably highly correlated with it. We have not been able to find enough estimates of gang populations at the neighborhood level using reliable sampling methods to observe a distribution. Generating such data in the future would enable us to test the model and help us to determine its accuracy.

Of course, all of this is contingent on the assumption that we actually have interventions that can reduce gang membership. The question of how effective such interventions are is a complicated one that goes well beyond the scope of this paper. However, at the very least, incarceration removes an individual from active participation in a gang in open society for the duration of the incarceration. Lipsey (1992), in a meta-analysis of almost 500
programs, found that certain types of delinquency programs do consistently reduce rates of recidivism.

Although we have confined our analysis here to the problem of street gangs, the basic approach may be relevant to a variety of social problems. This is particularly true of social problems that are contagious. The dynamics of contagion generate the possibility of multiple equilibria and, thus, epidemics and hysteresis under a broad range of conditions (Crane, 1989; Granovetter, 1978; Rogers and Rowe, 1993; Rowe et al., 1989, 1992a, 1992b; Rowe and Rodgers, 1991a, 1991b; Schelling, 1978).

REFERENCES


