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Size and the Density of Interaction in Human Aggregates[1]

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A baseline model is developed to show the conduciveness of population size to the density of interaction in human aggregates. This model permits deduction and, therefore, explanation of a wide variety of social phenomena. It explains the positive relation between rates of crimes of violence and city size indicated by Webb's (1972) data. And it provides a formal rationale for Kasarda's (1974) hypothesis relating size and communication in macrostructures, as well as an alternative to some aspects of the theory formulated by Hamblin, Jacobsen, and Miller (1973). Our model accounts for the "transitory" and "superficial" nature of urban social relations commented upon by Simmel (1903), Wirth (1938), and Milgram (1970) and explains why inhabitants of large cities are unlikely to intervene in crises. In conjunction with considerations noted by Mayhew et al. (1972), the model explains why role strain may be expected to increase with organizational size, as illustrated in Snoek's (1966) national study. The wide variety of phenomena illuminated by this model suggests that it is a serious mistake to view the effects of population size as "obvious." Rather, taking population size explicitly into account should enhance the explanatory power of sociological theories.

An extensive literature, both classical and contemporary, has called attention to the relationship between the size of human aggregates and a variety of sociological phenomena presumed to be direct consequences of size itself (e.g., Simmel 1903; Wirth 1938; Meier 1962; Milgram 1970; Kasarda 1974). Milgram has summarized a variety of evidence suggesting that the size of urban aggregates has exactly those effects previously claimed by Simmel and Wirth: most notably, decreased interaction time and increased anonymity. Similarly, Kasarda has provided indirect evidence of structural growth as a consequence of the proliferation of communication networks indicated by Meier.

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While the work of both Milgram and Kasarda surpasses earlier efforts in bringing more systematic data to bear on the questions they address, they follow the example of their predecessors in assuming that the potential effects of size are sufficiently obvious that they require no explicit formulation. That this is not the case will become clear from the fact that an explicit statement of the structural conduciveness of size to increased density of interaction reveals far more in the way of explanation than may be obtained through the implicit assumption.

The objective of the present inquiry is to develop a model of the conduciveness of population size to the density of interaction in human aggregates. Having done this, we shall indicate a wide variety of social phenomena that are explained by deductions from the model, including such variables as abbreviated interaction time in urban settings, role strain, violent crime, and growth rates of federal bureaucracies. The rationale for this undertaking is that it should show how sociologists can increase the scope and rigor of their explanations by taking population size explicitly into account in theory construction.

A BASELINE MODEL OF EXPECTED CONTACT

In order to establish an expectation for the number of contacts (encounters, links, interactions, etc.) that may occur among the elements of a population aggregate, we must have maps of all the logical possibilities. Such maps are supplied by the mathematical theory of graphs. To paraphrase Harary (1967, p. 3) a graph consists of a finite set of points and a set of lines, each of which joins two distinct points. The number of points in a graph is here interpreted as the size of a population aggregate. Similarly, the number of lines indicates the number of contacts among population elements. All distinct (nonisomorphic) graphs of order four (population size four) are shown in figure 1. These graphs map the number of distinct ways in which contacts or interactions of any kind can occur in a population of size four, varying from no contacts at all to contacts between every pair of population elements.

A baseline model for the expected number of contacts in a population of a given size is established by assigning the same probability of occurrence to each distinct graph that can be mapped on that population. This procedure makes the likelihood of any given contact configuration (line configuration) uniform; the way in which contacts occur is random. This permits us to determine how many contacts to expect by chance alone.[2]

For convenience of exposition, we adopt the following symbols and their

[2] The type of model described here is the same as those developed by early mathematicians to establish baselines for the study of any natural phenomenon (e.g., Laplace 1812, pp. 349–62).

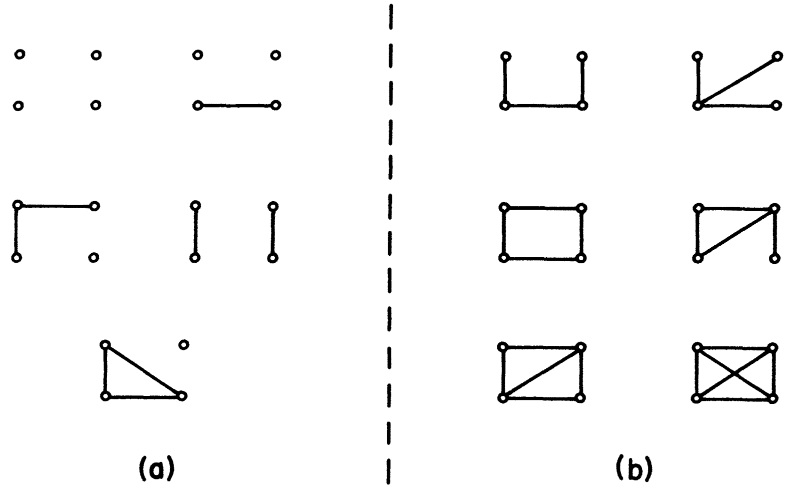

FIG. 1.—All distinct graphs of order four (size four)

definitions: $S =$ the number of population elements, that is, the order of a population's graph; $L =$ the number of contacts in a distinct population of given S, that is, the number of lines in a distinct graph with S points; $N =$ the number of distinct graphs mapping contacts in a population of size S; and, $C =$ the expected density of interaction, that is, the number of contacts that would be expected to occur in a population of size S by chance alone. Observe that the maximum number of contacts ($L_{\max}$) which can occur in a population of size S is

$$L_{\max} = \frac{S(S-1)}{2}. \tag{1}$$

Let $g = 1, 2, 3, \ldots, N$ be an index for the distinct graphs that can be mapped on a population of size S, and let p_g be the probability of g. As indicated previously, we establish a baseline model for the contacts in a population by assigning the same likelihood of occurrence to each g of S. Accordingly, we define the probability density function

$$p_g = \frac{1}{N}, \tag{2}$$

which generates the underlying line distribution for the g's that map S. This line distribution is symmetric about its mean (Harary 1955, p. 451), from which it is determined that the expected number of contacts (or lines) in a population of size S is

$$C = \frac{L_{\max}}{2}, \tag{3}$$

that is, the number of contacts, interactions, encounters, etc. that we expect to occur by chance alone in a population of size S.

Equations (2) and (3) permit us to establish basic theorems concerning the conduciveness of aggregate size to the density of interaction in human populations.[3]

Aggregate theorem 1: Expected density of interaction is an increasing function of aggregate size.

That is, the rate of change in C with respect to S is positive; specifically,

$$\frac{dC}{dS} = \frac{S}{2} - \frac{1}{4}. \tag{4}$$

This leads to the next theorem:

Aggregate theorem 2: The rate of increase in the expected density of interaction with respect to aggregate size is an increasing function of aggregate size.

That is, the rate of change in the rate of change is positive; specifically,

$$\frac{d^2C}{dS^2} = \frac{1}{2}, \tag{5}$$

from which it is clear that:

Aggregate theorem 3: As aggregate size increases without bound, expected density of interaction increases without bound.

Specifically,

$$\lim_{S \to \infty} C = \infty. \tag{6}$$

The implications of these theorems are illustrated in figure 2, which graphs equation (3) as a function of size. As figure 2 clearly illustrates, an additive increase in aggregate size is accompanied by a multiplicative increase in the expected density of interaction. In other words, as the size of a population aggregate increases, its interaction potential increases at an increasing rate.

Equation (3) also permits us to arrive at the interaction potential of individual population elements, that is, the *expected number of contacts*

[3] Because we are using nonisomorphic graphs, the distinct structural forms illustrated in fig. 1, it might be thought that we have not adequately considered all configurations of events, due to the fact that individual points are not identified. However, the underlying line distribution for labeled graphs (graphs in which each point is identified) is also symmetric about its mean and its mean is identical to equation (3). All our results will be the same for labeled or unlabeled graphs. Also, Kephart's (1950) work might lend the impression that graphs, because they are based upon dyadic relations, do not consider all the possibilities for interaction among subsets in the aggregate. The impression is incorrect, for Kephart was making additional assumptions. There is no configuration of interaction among population elements that is not taken into account by the underlying line distribution of graphs.

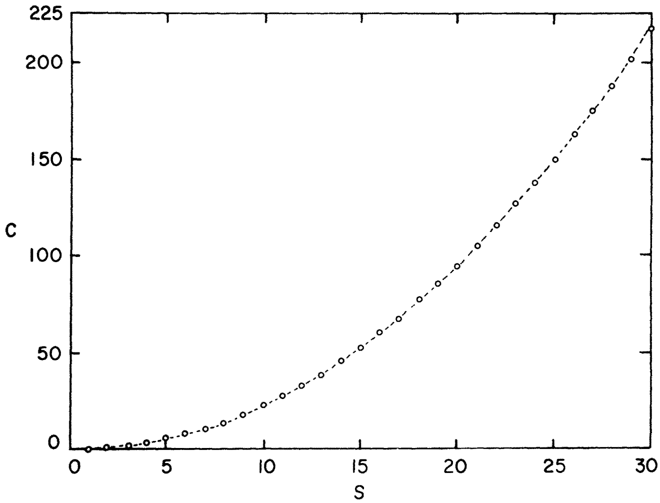

FIG. 2.—Expected interaction density (C) as a function of aggregate size (S)

or interactions per population element. This expected number will be called *expected element density* (symbolized D) and is given by

$$D = \frac{(S - 1)}{2}. \tag{7}$$

This leads to the conclusion that:

Aggregate theorem 4: Expected element density is an increasing function of aggregate size.

That is, the rate of change in D with respect to S is positive. Specifically,

$$\frac{dD}{dS} = \frac{1}{2}, \tag{8}$$

which leads to the further conclusion that:

Aggregate theorem 5: The rate of increase in expected element density with respect to size is a constant.

That is, the rate of change in the rate of change is zero:

$$\frac{d^2D}{dS^2} = 0. \tag{9}$$

Accordingly,

Aggregate theorem 6: As aggregate size increases without bound, expected element density increases without bound.

Specifically,

$$\lim_{S \to \infty} D = \infty. \tag{10}$$

In contrast to the multiplicative effect of aggregate size on the expected density of interaction in the population as a whole, additive increases in aggregate size yield additive increases in expected element density, the expected number of contacts per population element.

However, since finite population elements, such as humans, are by definition entities with a finite amount of time to devote to the total stream of incoming contacts specified in equation (7), it is necessarily the case that the expected proportion of time (symbolized A) an element can devote to each contact is a decreasing function of aggregate size, according to the equation

$$A = \frac{2}{(S-1)}. \tag{11}$$

Thus:

Aggregate theorem 7: Expected time per contact is a decreasing function of aggregate size.

That is, the rate of change with respect to aggregate size is negative:

$$\frac{dA}{dS} = -\frac{2}{(S-1)^2}. \tag{12}$$

Furthermore:

Aggregate theorem 8: The rate of decline in expected time per contact is an increasing function of aggregate size.

That is, the rate of change in the rate of decline is shifting toward zero:

$$\frac{d^2A}{dS^2} = \frac{4}{(S-1)^3}. \tag{13}$$

Finally:

Aggregate theorem 9: As aggregate size increases without bound, expected time per contact approaches zero.

That is,

$$\lim_{S \to \infty} A = 0. \tag{14}$$

The general implications of these trends are illustrated in figure 3, which graphs equation (11) as a function of aggregate size. As figure 3 clearly shows, an additive increase in aggregate size generates a precipitous decay in the expected proportion of time a population element has for each potential contact. As aggregate size increases, the expected proportion of time per contact rapidly approaches zero.

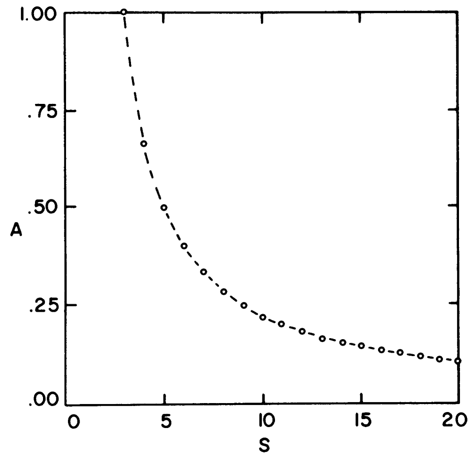

FIG. 3.—Expected proportion of time per contact (A) as a function of aggregate size (S).

TRANSITION

Our model is stated in abstract theoretical terms and we must effect a transition to the "observables" of concrete social life. Doing so requires that we first clarify several points about the nature of the model itself.

Maximum and Potential

Our "expected density of interaction" given in equation (3) is a statistical expectation based upon two critical items of information: (*a*) the maximum possible number of direct contacts is $[S(S-1)]/2$, and (*b*) the underlying line (contact) distribution is symmetric about its mean (again, see Harary 1955, p. 451). Knowledge of the maximum possible number of contacts is necessary but not sufficient to derive a statistical expectation for the number of contacts (relations, interactions, etc.) in a population aggregate. Without knowledge of the underlying line (contact) distribution, we cannot arrive at such an expectation. Accordingly, our model is not merely a reaffirmation of the well-known fact that the maximum possible number of contacts in a population of size S is $[S(S-1)]/2$.

Rather, our model corrects what appears to be a common misconception in the social science literature (e.g., Graicunas 1933; Caplow 1956; Mott 1965): the maximum possible number of contacts is *not* an estimate of the "potential" number of contacts in either an aggregate or an organized social system.[4] The maximum possible number of contacts (or relations)

[4] Our use of the term "aggregate" is to distinguish between populations in general, illustrated in fig. 1, and populations which are connected social systems, illustrated in fig. 1*b*. The underlying line distribution for connected graphs is not symmetric about

is relevant only to special categories of human groups. For example, Bossard (1945) used it correctly because: (*a*) he was not discussing a statistical expectation, and (*b*) he was discussing primary groups.[5] Our statistical expectation is not confined to special cases. It refers to all human aggregates, whether or not they are organized social systems.

Dynamic Density

We interpret the statistical expectation for density of interaction as a theoretical expectation for what Durkheim called "dynamic density" (1893, p. 283). However, our theoretical expectation is based upon knowledge of aggregate size alone. It is not based upon all the factors Durkheim considered relevant to the production of dynamic density (1893, pp. 283–99). But there is no reason that it should be. We are interested in examining the effects of size, not the effects of other factors.

Nevertheless, other factors are important and require comment. We do not expect that aggregate size alone will have total and deterministic effects. Both physical distance and level of contact technology should have marked effects on (observed) density of interaction (Hawley 1971). The Law of Distance-Interaction states that the likelihood of interaction or contact of any kind between two social elements is a multiplicatively decreasing function of the distance between them, or of the costs of overcoming that distance (Carrothers 1956). This proposition holds over time and cross-culturally.[6] The effects of distance are not merely present, they are profound, and they are documented by reams of empirical research (see Olsson 1965). The effects of distance pervade all aspects of social life, from marriage to crime (Turner 1969) and from the distribution of

its mean and gives rise to additional theorems not considered here. For present purposes, we need only note that for size 10 or larger, there are no noticeable differences between the expected number of contacts in connected social systems and population aggregates in general.

[5] Bossard's statement of the Law of Family Interaction is as follows: "With the addition of each person to a family or primary group, the number of persons increases in simple arithmetic progression while the number of personal interrelationships within the group increases in the order of triangular numbers" (1945, p. 292). This is a deterministic relation based upon the definition of a primary group as a system in which *all members stand in the same social relation to one another*. A primary group exists only if all members maintain reciprocal personal relations with one another, as Bossard's statement clearly specifies (cf. Cooley 1909, p. 23). For this reason it is definitionally determined that the number of relations in a primary group is always the maximum number. However, since personal social relations cannot be sustained on this scale in large aggregates, Bossard's law applies to a very restricted size range, and Bossard never claimed otherwise.

[6] In ancient Mesopotamia (Johnson 1972), in pre-Columbian America (Marcus 1973), in preindustrial Europe (Braudel 1966), and in contemporary societies, both agricultural (Johnson 1970) and industrial (Zipf 1949).

medical doctors (Kühne 1937) to the evolution of empires (Taagepera 1968).[7]

By "level of contact technology" we mean the relative efficiency of the technical means of communication and transport in overcoming the "drag effect" of distance. While increases in the relative efficiency of this technology have never reduced the effects of distance to zero in any society, both over-time and cross-cultural differences in the level of contact technology have sharp ratchet-like (step function) effects in reducing the impact of distance on interaction (Hawley 1971). Consequently, however powerful the effects of aggregate size may appear to be in our subsequent examples, a thorough analysis of interaction density would ultimately involve the variables of distance and level of contact technology (Schnore 1958).

Structural Conduciveness

Our model of interaction potential is a model of structural conduciveness. It says that increases in aggregate size (over time or cross-sectionally) are conducive to increases in the number of contacts or interactions. It says nothing about why people engage in such contacts or interactions in the first place. It predicts, for example, that as aggregate size increases additively, both the number of phone calls and the number of homicidal assaults will increase multiplicatively. But it says nothing about why people make phone calls or commit homicide. Rather, a model of structural conduciveness merely shows that, given a nonzero propensity to sustain contacts, aggregate size multiplies the opportunities for those contacts to be realized. Accordingly, we would predict that they will in fact be realized more often in larger aggregates.

This is not to say that there are no criteria for applying the model to particular aggregates. Durkheim (1893) has already supplied two criteria that specify how well it should work. First, the larger the distance between population elements, the lower is the likelihood that the model will apply. This rules out most arbitrary attempts at gerrymandering. Second, the higher the level of contact technology within an aggregate, the greater the probability that the model applies. However, the principal criterion must always be theoretical relevance. If an aggregate is deemed a meaningful system of interaction to which other sociological theories are applicable, then the model should apply to that aggregate. Thus, if cities are meaningful units for sociological analysis, as sociological theories about communities would claim, then our model applies to cities. Otherwise, it would

[7] We do not include the effects of distance here because models for estimating the effects of distance already exist (e.g., Beckman 1968; see also von Thünen 1826; Weber 1909; Christaller 1933; and Lösch 1940).

not. The same criterion holds for groups, organizations, associations, and even whole societies. Our model is intended to supplement other theories about interaction systems. It is not proposed as an alternative to them.

Lines of Contact

The lines of contact or communication illustrated in figure 1 may be very transitory or very stable. Transitory contacts could vary from eye contact among sidewalk strollers to homicidal assaults between strangers, or from ticket purchases in an airport to casual conversations at a cocktail party. Stable contacts range across the entire spectrum of social organization, from lines of communication among employees in formal organizations to interaction among family members.

The expectation for lines of contact given in equation (3) refers to all contacts sustained in an aggregate at a given point in time, regardless of whether some are stable and others transitory. On the other hand, this does not mean that the observed number of contacts enumerated in an empirical study will exactly correspond to the expected number in equation (3). It probably would not, partially for reasons given in theorems 7–9 and discussed in the next section. However, the multiplicative increase predicted in equation (3) is used to estimate the number of contacts we expect to occur empirically. This is not because we think that the expected and observed numbers will exactly correspond, but we expect the observed number to grow according to the function given in equation (3). The observed and expected numbers should differ by no more than a linear change of scale. For this reason, it is the form of the function in equation (3)—not the exact number it yields—which serves as a guide to prediction.

Similarly, all subsets of contacts will be estimated by the same function (eq. [3]). For example, we expect the number of pairs mapped by the relation of "kissing" to grow according to the same function which predicts an increase in the number of pairs mapped by the relation "homicidal assault." The reason for this is that—for present purposes—the only difference in types of human contacts is the amount of time and energy required to sustain them, and these considerations are governed primarily by physical distance and level of contact technology.

Prediction

There are limits to growth in any finite system (von Bertalanffy 1950, pp. 144–46). Multiplicative growth will stop short of infinity. The same contingency applies to linear increases in scale. Ultimately, therefore, finite systems cannot maintain even linear increases in their principal components. These restrictions on growth apply to relationships among finite population elements (Goldsmith 1971). Initially the actual volume of contacts may grow according to the multiplicative increase indicated in equation (3). But the decay function in equation (11) guarantees that such growth cannot be sustained indefinitely. As aggregate size increases, theorems 7–9 rapidly depress time per contact, so that the rate of increase in contacts must attenuate.

The interaction of equations (3) and (11) should therefore have distinct empirical consequences. The observed density of interaction (symbolized C_o) should initially increase at a multiplicative rate, but ultimately diminish to a relatively slow pace. Consequently, the relationship between observed density of interaction and aggregate size will be described by an S-shaped logistic curve, as illustrated in figure 4. Both the observed

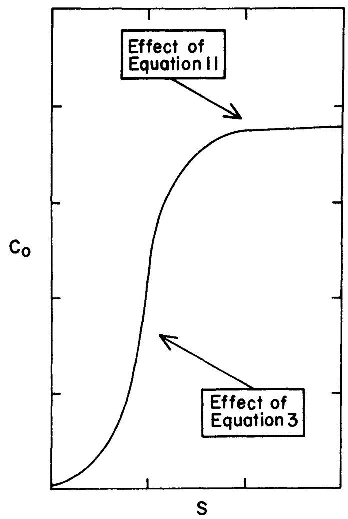

FIG. 4.—Predicted relationship between observed density of interaction (C_o) and aggregate size (S).

volume of kisses and the observed volume of homicidal assaults might then be reasonably[8] approximated by the function:

$$C_o = a + b(\ln S), \tag{15}$$

[8] The logistic curve in fig. 4 has an upper bound, while the logarithmic transform in equation (15) does not (the mathematical properties of logistic curves are given in James and James 1968, p. 223). Equation (15) is suggested as an approximation because: (1) in the presence of measurement error and limited variable range, it may be difficult to distinguish between the logistic curve and the simple logarithmic transform; and (2) it is the closest approximation to the logistic curve we are likely to find employed in the studies we wish to cite as examples in subsequent discussion. Note that equations (15) and (16) are not part of our baseline model. They are not mathematically derived from it. They are our estimates of what the data are likely to show as a result of the interaction of equations (3) and (11).

at any given point in time, with the constants *a* and *b* determined by such considerations as (1) average distance among population elements and (2) level of contact technology.

The linear increase in element density predicted in equation (7) is subject to the same general restrictions. While the observed number of contacts per population element (i.e., observed element density, symbolized D_o) may initially grow according to equation (7)'s linear function, beyond some point in size the decay function in equation (11) will have its inevitable attenuating effect. The empirical result will be a relationship of the form shown in figure 5, which graphs observed element density as a function of aggregate size. The initial linear increase in observed element density will begin to level off under the impact of equation (11) in the upper range of size.

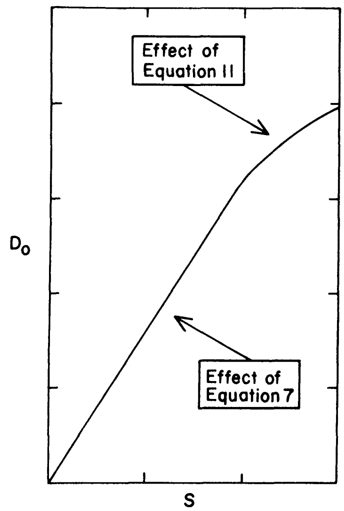

FIG. 5.—Predicted relationship between observed element density (D_0) and aggregate size (S).

However, because the initial increase in observed element density is predicted to be linear, there may be no well defined function which adequately describes the empirical result illustrated in figure 5. On the other hand, it is possible that equation (11) will begin to have its effect relatively low in the size range. Should this occur, the relation between observed element density and aggregate size *might be* of the general form:

$$\ln D_o = a + b(\ln S), \tag{16}$$

with the constants *a* and *b* determined by the same considerations suggested for observed density of interaction. However, this can only be empirically determined.

EMPIRICAL ILLUSTRATION

In the examples which follow, we shall see that deductions from our model predict variation in many types of social phenomena. In this sense, our model constitutes an explanation for the variation observed (Hempel and Oppenheim 1948). However, as indicated previously, we are not suggesting that aggregate size provides all the explanation. Our model is no more than an attempted first step toward unraveling the determinants of dynamic density.

Violent Interaction

Violent contacts are a subset of all human contacts and may serve as a beginning example of our model's applicability. Civil authorities keep records on some types of violent contacts and criminologists have suggested that violence may be an emergent property of social interaction (Ball-Rokeach 1973, p. 748). Bearing in mind that the reporting of crimes leaves much to be desired in the way of accuracy (Black 1970), we may consider the homicide potential, robbery potential, and assault potential of population aggregates.

In the United States of North America, violent crimes such as murder, robbery, and aggravated assault are usually reported as rates, ordinarily as the number of such crimes per 100,000 population. The decision to report violent crimes in this fashion directly reflects the assumption that increased population creates increased opportunities for such crimes. Furthermore, the expression of crimes per 100,000 population makes explicit the assumption that the effect of aggregate size is additive. As equation (3) shows, this is a false assumption. The opportunity structure for murder, robbery, and aggravated assault increases at an increasing rate with aggregate size. Accordingly, theorem 2 leads to the deduction that murder rates, robbery rates, and assault rates as usually expressed will be increasing functions of city size because they do not take the multiplicative effect of aggregate size into account.

As illustrated in table 1, where the indicated rates are compared for various size categories of U.S. cities in 1970, with the exception of the reversal in the two lowest size categories under aggravated assault, the trends verify the prediction deduced from theorem 2. The size categories in table 1 are crude, but this does not invalidate our comparison. If the effect of population size were only additive, then no trends would appear regardless of the intervals employed. But they do appear, and in the direction predicted by theorem 2. However, crude categories do not permit us to evaluate the nature of the relationship itself. A recent study by Webb (1972) permits us to examine this question.

TABLE 1

RELATIONSHIP BETWEEN SELECTED VIOLENT CRIME RATES AND CITY SIZE CATEGORIES IN THE UNITED STATES, 1970

CITY SIZE CATEGORY (POPULATION)	SELECTED VIOLENT CRIME RATES*		
	Murder	Robbery	Aggravated Assault
250,000 or more	17.5	589	334
100,000–249,999	10.0	199	218
50,000–99,999	5.2	110	143
25,000–49,999	4.2	82	117
10,000–24,999	3.3	42	105
Less than 10,000	2.6	24	108

SOURCE.—U.S. Bureau of the Census (1973, table 226).
* Crimes known to the police per 100,000 population.

Webb studied 682 urban places in the United States, all with populations of 25,000 or larger. In spite of this restricted size range, he found (1972, pp. 650–51) that a logarithmic transformation of aggregate size explained more variance in violent crime than any other factor. That is, violent contact—as measured by violent crime—was best predicted by aggregate size through the form of the relation specified in equation (15), the results we expect on the basis of theorems 2 and 7 (from eqs. [3] and [11]). Webb's finding was not particularly strong ($r = .44$), but this may be partially attributed to the limited size range in his data.[9] A more extended range is required for a full test of the relation. In any case, his data confirm the predictions from our model indicated in equation (15).

Abbreviated Interaction Time

Simmel (1903, pp. 188–89) and Wirth (1938, p. 1) noted the decline in interaction time (per contact) associated with increases in city size. They drew attention to the superficial and transitory nature of urban interaction and to increased anonymity. Milgram has more recently taken up their theme, and it is our intention here to show that our model formalizes the general nature of their observations.

Milgram attempts to account for many regularities in the behavior of urban dwellers by reference to the effects of aggregate size (which he simply assumes) and to the concept of information overload. He summarizes the nature of responses to input overload created by aggregate size as follows: "One adaptive response to overload . . . is the allocation of less time to each input. A second adaptive mechanism is disregard of

[9] The relatively weak relation might also be due to Webb's use of a composite index of violent crime (1972, p. 646). Aside from the fact that the opportunity structure for forcible rape is different from the other types of crimes, aggregating rates in this fashion could weaken the relation.

low-priority inputs" (1970, p. 1462).[10] In other words, one response to the interaction storm created by aggregate size involves reduced time for any given input. This response is offered in explanation of the superficial and transitory character of urban social relations.

We would not deny that the responses in question describe the behavior of individuals adjusting to overload (see Miller 1956; Miller 1962; Broadbent 1971). However, Milgram is merely describing a process; he is not providing an explanation for its occurrence. Our concern here is to note that the decreased interaction time of urban dwellers is logically implied by our theorems 7–9; our model constitutes an explanation of decreased interaction time per contact. That is, since humans are by definition finite organisms with a finite amount of time to devote to the total stream of incoming signals, it is necessarily the case that the average amount of time they can devote to the increasing volume of contacts specified in equation (7) is a decreasing function of aggregate size according to equation (11). This will occur by chance alone.

Furthermore, it tells us why the vast majority of contacts in large urban centers cannot be based upon "primary" social relations. By definition, primary relations require a great deal of time in interaction to be sustained. This does *not* imply that all primary contacts will disappear with increases in aggregate size. It does imply that *most* contacts will not have the nature of primary social relations.[11]

And this consequence of our model also explains why anonymity is expected to be an increasing function of aggregate size. As size increases, average time per contact tends toward zero. The finite processing capacity of the human nervous system receives smaller and smaller amounts of information about each additional person encountered, and in very large aggregates many of the potential pair contacts are never even realized. Thus, as aggregate size increases it will ultimately reach a point where attaching labels to unique individuals surpasses the input-and-retrieval

[10] Milgram actually lists a total of six adaptive responses to overload. However, the four others are either (1) special cases or interpretations of the two listed in the text, or (2) responses not of individuals but of social systems (cf. Meier 1962). Furthermore, the second of the two listed in the text is not peculiar to contact overload. Rather, it is a constant feature of the human nervous system acting to filter overloads of all types (see von Foerster 1966).

[11] It should be noted that this consequence of our model is in no way inconsistent with the findings of Kasarda and Janowitz (1974). Their work suggests that there is no reason to expect a decline in sociability with increasing aggregate size. This is not the same thing as the relative frequencies of primary and secondary relations in the work of Tönnies (1887) and Wirth (1938). The prediction from our model is that the relative number of primary contacts will decline—not the absolute number. The absolute number of primary contacts may well increase with size. A relative increase in secondary contacts in no way implies a decline in the absolute number of primary contacts. Our model is therefore consistent with Tönnies, Wirth, and Kasarda and Janowitz.

capacity of the human nervous system.[12] Beyond this point, it follows that the proportion of the population any person can identify is a decreasing function of size and, therefore, that anonymity is an increasing function of size. Theorems 7–9 (from eq. [11]) formalize the relation between aggregate size and anonymity.[13]

Returning to Milgram's (1970) discussion, another aspect of urban life which he attributes to reduced time available for any given contact is the failure of urban dwellers to intervene in a crisis. The example he cites is the failure of Kew Gardens residents to render aid in the 1964 Genovese murder in Queens, New York. The question is more general and is answered by the observation that the expected amount of time a person (selected at random) will devote to a contact (selected at random) is a rapidly decreasing function of size. Our theorems 7–9 formalize this prediction; they provide a deductive explanation for failure to intervene in crises in large aggregates. Thus, if we insert the 1964 population of metropolitan New York into equation (11), we discover that even on the basis of a 24-hour day, the average amount of time a New Yorker would be expected to devote to a signal (contact) selected at random is considerably less than it takes to phone the police.

Our primary concern in this section has been to indicate how our model formalizes many existing notions and observations about abbreviated interaction time and its consequences. Actual data are thin. Milgram (1970) has summarized most of the studies in this area, and some of them are relatively inconclusive.[14] However, there is one study which confirms our predictions on the consequences of abbreviated interaction time (Dodd 1957). As aggregate size increases, declining time per contact forces individuals to respond to fewer and fewer of the social signals which impinge upon them. The larger the aggregate, the lower is the probability that a person selected at random will respond to a contact selected at random—as we have argued above in discussing crises. Dodd's (1957) study of leaflet

[12] It has long been recognized that time sequence in the action of the human nervous system is critical to all its operations (von Monakow 1914) and that humans, like computers, take in information in serial order (Simon 1974). The basic problem with respect to anonymity arises not from memory capacity alone but from time sequence patterns in the input of information into primary memory, throughput to secondary memory, and retrieval of information from secondary memory. The frequency and duration of contacts are therefore critical. Time per contact governs anonymity and our model specifies time per contact as a function of aggregate size.

[13] Anonymity itself may be expected to have structural consequences. The use of uniforms for identifying categories of persons is one information standardization device found in large, complex systems (Joseph and Alex 1972).

[14] This is due, we think, to the relatively small size differences involved. Perhaps the strongest demonstration of the effects of anonymity in a large aggregate is provided by Turner's (1969) study of delinquency. However, his data are from one city and do not permit evaluation of our model.

drops on six cities ranging in size from 1,304 to 325,994 confirms this prediction. He finds that the proportion of persons responding to an extraneous social contact is a monotonically decreasing function of city size.[15] This is a direct confirmation of the consequences implied in theorems 7–9.

Aggregate Size and Role Strain

Goode identifies two basic conditions that contribute to role strain, that is, to "felt difficulty in fulfilling role obligations" (1960, p. 483). One condition has to do with the inherent contradiction contained in diverse expectations that attempt to elicit (logically) mutually exclusive responses (e.g., Field 1953). The second condition has to do with time overloads generated either by many different obligations or by obligations that call for different behaviors simultaneously (e.g., Killian 1952). We shall consider both of these conditions.

From our model we see that as size increases, the number of persons who may be expected, by chance alone, to transmit expectations to any one member of the aggregate increases according to the linear function in equation (7). Furthermore, since each of the expectations will require for its fulfillment some nonzero amount of time, and since the role incumbent is a finite organism, it follows that the amount of time that the expectations will ultimately come to require is greater than the time available to the role incumbent. Similarly, as equations (11)–(14) show, as the number of expectations increases with aggregate size, the average amount of time the role incumbent will devote to each, by chance alone, will steadily shift toward zero, a condition hardly likely to please the transmitters of the expectations. Thus, our model predicts that as size increases, the total amount of time that will be demanded of the role incumbent will ultimately exceed his capacity *and* that the total amount of time he has available to satisfy any given demand steadily declines. We can think of few conditions more likely than these to lead to "felt difficulty in fulfilling role obligations." Our model predicts that role strain due to time pressure will be an increasing function of aggregate size.

Mayhew et al. (1972) developed a baseline model of the relation between aggregate size and structural differentiation. Instances of structural

[15] Although there is insufficient space to give a detailed outline of Dodd's (1957) study design, it should be noted that he began with the assumption that the relevant set of relations is the maximum number, to which he added the idea that people communicate with themselves. Consequently, the expectation he used was the function S^2. At large values of size, as in Dodd's study, our own model differs from this value by no more than a linear change of scale, because S^2 is the upper limit of our $L_{\max}$ in equation (3). In verifying his own model, Dodd directly verified ours.

differentiation included differentiation of the population into roles, statuses, subgroups, etc. Their model showed that (1) structural differentiation is an increasing function of aggregate size and (2) the rate of increase in structural differentiation is a decreasing function of size. These relations will hold by chance alone. According to both Merton (1957) and Goode (1960), an increase in role differentiation may be expected to lead to an increase in role strain due to increased possibilities for contrary expectations. Thus, the Mayhew et al. (1972) model leads to the prediction that role strain due to contrary expectations will be an increasing function of aggregate size.

To summarize, from our model on the relation between size and expected density of interaction and from the Mayhew et al. (1972) model on the relation between size and structural differentiation, we can logically deduce that role strain due to both time overloads and contradictory expectations will be an increasing function of aggregate size. These two models formalize the relation between aggregate size and role strain.

Snoek's (1966) national study of role strain in work organizations (1) shows a positive relation between role strain and organization size and, (2) presents no analysis which can be interpreted to show effects due to factors other than size.

Relying upon a 1961 sample of persons 18 or older living in private households in the United States, Snoek selects for his analysis the subset of persons who would be classified as (approximately) full-time wage or salary workers (a total of 596 persons). The focus of his analysis is on the role incumbent in the work organization and the expectations impinging upon the incumbent on the job. The variables he considers include (1) role strain, (2) organizational size, (3) role-set diversity (role differentiation among the incumbent's "role-senders"), (4) the incumbent's level of supervisory responsibility, and (5) frequency of interaction between the role incumbent and each category of his role senders. Snoek (1966, p. 365) offers two hypotheses: (1) that role strain will be an increasing function of role-set diversification and (2) that role strain will be an increasing function of organizational size. We have no objection to these hypotheses, but the first hypothesis must be supported independent of size.

Snoek (1966, pp. 367–68) begins with an analysis of the relation between role strain and the frequency of interaction within each of his five classes of role senders. In every role-sender category, there is a positive relation between role strain and interaction frequency, showing statistical significance in four out of five categories. The main point to note from this finding is that increased interaction frequency may reflect nothing more than the increased numbers of persons with whom interaction is sustained, that is, the size of the interacting aggregate in each category. Thus, the first phase of Snoek's analysis is quite consistent with our size hypothesis and does not permit the interpretation that interaction frequency accounts for the results independent of size.

Snoek next considers the relation between (1) role strain and role-set diversity and (2) role strain and level of supervisory responsibility while controlling for role-set diversity. He finds a significant positive trend in both cases. However, since role-set diversity and number of supervisory levels are both instances of structural differentiation, the Mayhew et al. (1972) model predicts an increase in both as a function of size. The correlation between role strain and role-set diversity and between role strain and level of supervision may reflect nothing more than this aspect of size. Again, it is not clear that any variable other than size is operating.

Snoek also examines the relation between role strain and company size, finding a significant positive trend. This confirms the predictions of the two proposed size models, although it does not permit us to interpret the kinds of effects specified by each model because Snoek's measure of role strain does not distinguish between strain due to time overloads and strain due to contrary expectations.

Snoek then attempts to control for company size by collapsing his original set of size categories (with ranges 1–9; 10–49; 50–499; 500–4,999; and 5,000+) into two, labeled small (less than 500) and large (500+). Within each of these two gross size categories, Snoek examines (1) the relation between role strain and role-set diversity and (2) the relation between role strain and level of supervisory responsibility. In both instances he finds a positive relation within each size category. However, considering the size variability within each of the gross categories, and the predictions of the Mayhew et al. (1972) model for both types of differentiation, these results within size categories may still be due to nothing more than size. And, in the comparison *across* the two gross size categories (within each of the role-set diversity and supervisory level categories), the trend for a positive relation between role strain and size continues to hold for four out of six comparisons—in all three categories of supervision level and in one out of three role-set diversity categories—although statistical significance is achieved only in the comparison within the highest role-set diversity category. The trend continues to hold in the majority of cases, and since much size variation is concealed within gross categories, the extent of the trend may be underestimated. Owing to the mode of analysis, effective control for size is not achieved.

As far as Snoek's analysis goes, (1) it confirms the predictions of the two size models we have discussed, and (2) given his mode of analysis, there are no conclusions that can be drawn about factors which operate independent of size.

Communication and Coordination

Students of industrial society have remarked upon the rapid expansion of coordinative and communicative occupational specialties during periods of demographic and economic growth. Wagner (1892, p. 893) suggested that, under conditions of modern technology, state activity will expand both intensively and extensively. Thus, government spending in England grew by a factor of 6 between 1700 and 1800, while population grew by a factor of 2 and average real output in various economic sectors grew by a factor of 1.47 (Deane and Cole 1967, pp. 65, 76–78). In the United States, the number of federal employees grew by a factor of almost 500 between 1816 and 1961 while population grew by a factor of 20; and between 1940 and 1966 the number of state and local government employees grew more than 150% while population increased by only about 50% (Lenski 1970, pp. 365–366). There has been a corresponding tendency for the rapid expansion of tertiary or service occupations to be associated with intensive industrialization (Sauvy 1949; Deane and Cole 1967; Du Boff 1973).

Explanations for these structural changes have been various and uneven in quality. Sauvy (1949, p. 59) attributes the disproportional growth of the service sector of the economy to technological changes, while Lenski attributes disproportional increases in government to "the rise of the new democratic ideology" (1970, p. 366). Du Boff attributes all structural changes, including these, to an international capitalist conspiracy (1973, pp. 6–9, 19–24). There are other arguments, but we cannot review them here.

To the extent that population increases, multiplication of contacts and interaction of all kinds is predicted by our model in theorems 1–3, and many structural correlates may be expected. Task specialization with respect to communication functions is the clearest expectation, and Kasarda's recent analysis at three levels of system organization is a direct confirmation of this expectation. He finds that the proportion of the labor force in communication specialties is an increasing function of size for formal organizations, communities, and nations (1974, pp. 23–24). Furthermore, his finding (p. 24) that this correlation is with a logarithmic transformation of size directly confirms a structural response consistent with our expectations illustrated in figure 4 and specified in equation (15). And, just as his finding confirms our model, our model formalizes the underlying rationale for his analysis. His assumption (1974, p. 20) that difficulties of communication are likely to be the most important problems faced by expanding aggregates is correct to the extent that communication is predicted to grow multiplicatively and, ultimately, to exceed the information processing capacities of individuals (theorems 7–9). Structural adjustments to overload must be developed if the population is to maintain a communication network. To the extent that the solution takes the form of occupational specialization, it is clearly predicted from our model that task specialization with respect to communication is of primary importance. Our model makes the same prediction for all types of aggregates, and Kasarda finds that his hypothesis on communication specialties holds at three system levels.

The fact that the growth of (observed) interactive density must ultimately attenuate (figure 4) may bear upon Kasarda's finding that coordinative components of occupational structure do not necessarily behave in the same fashion across system levels (1974, pp. 23–25). However, this is a complex problem, partly on account of definitions of coordinative-administrative occupations and especially owing to the fact that social systems can respond to coordination problems in several ways other than by increases in the number of administrative personnel (see Rushing 1966*a*, 1966*b*). On the other hand, Kasarda's finding of a reversal of the relations for coordinative-administrative occupational groups at the level of communities and societies may be due to the shift in the definition of his size base for these systems. A fuller test of the question is required.

Hamblin et al. (1973) have developed a powerful diffusion model to explain occupational expansion over time. Their model predicts over-time growth in numerous occupational categories, including those with communication and coordination (e.g., governmental) functions (1973, pp. 96–100). And, their model predicts that these phenomena will approximate a logistic curve (pp. 56–57) over time, for the same (finite system) reasons we have posited in our model.

In some respects our model is an alternative to the theory proposed by Hamblin et al. (1973); in other respects the two models are complementary. For example, our model predicts changes with size both over time and cross-sectionally (as in Kasarda's study), while diffusion models are confined to over-time predictions. Nevertheless, a diffusion model seems quite reasonable for adoption of entrepreneurial occupations (e.g., shopkeeper, attorney). But even in these instances, occupations will not be adopted unless there is demand for their services in the population. Our model specifies the nature of this demand for communicative-coordinative occupations as a function of aggregate size. In many instances it seems more appropriate to say that a system adopts individuals—as in the military draft. More generally, both persons and social systems seem to simultaneously adopt one another, so that the outcome might be described as an emergent property of interaction, rather than as a directional diffusion process. However this may be, a size model like the one presented here indicates pressure on populations to generate task specialization with respect to both coordinative and communicative functions, independent of the specific nature of the adoption process.

There are yet firmer grounds for the view that our model is complementary to Hamblin et al. (1973). Tarde (1890, p. 19) suggested that the size and density of connections in a social system should affect the rate at which information—or any other item—diffuses in a population. He was correct: both rumors and viruses may be expected to move rapidly toward saturation level in large, densely connected aggregates. This is true on purely a priori grounds. The rate at which any diffusion process can occur is directly affected by both (1) the size of the population and (2) the density of connections (contacts) in that population. For this reason, a combination of our model with the Hamblin et al. (1973) diffusion theory should provide a stronger basis for prediction.

OVERVIEW

The interaction potential in a human population is a multiplicatively increasing function of aggregate size. The model we have presented to show this permits deduction and, therefore, explanation of a wide variety of social phenomena. The model predicts that rates for most violent crimes will be an increasing function of aggregate size, a prediction borne out in our illustration for U.S. cities and more specifically in Webb's (1972) study. The model predicts the reduced interaction time remarked by Simmel (1903), Wirth (1938), and Milgram (1970) in their attempts to describe the nature of urban life and is borne out by Dodd's (1957) study of six cities. It provides a formal explanation for anonymity, for the expected relative decline in primary contacts, and helps us understand why urban dwellers are unlikely to intervene in crises. The model predicts that role strain will be an increasing function of aggregate size and, in conjunction with the structural differentiation model of Mayhew et al. (1972), explains the findings in Snoek's (1966) national study. The model is verified by Kasarda's (1974) study of the relation between size and structural expansion of communication-related occupational specialties at three levels of system organization and provides an explicit deductive rationale for his hypothesis. Finally, our model appears to be an alternative to the diffusion model proposed by Hamblin et al. (1973) in some respects and complementary to it in others. A combination of the two models promises an increase in explanatory power. In summary, our model suggests that an explicit formulation of the effects of size provides far more in the way of explanation than does the implicit assumption.

In this paper we have followed the suggestion put forward by Durkheim (1898), Halbwachs (1938), Mackenroth (1953), Schnore (1958), Svalastoga (1965), and Kasarda (1974) that taking population structure directly into account is an important and legitimate line of sociological inquiry. As evidence accumulates, it becomes increasingly clear that aggregate size is a powerful explanatory variable, whether at the level of organizations (Blau 1970), communities (Abrahamson 1974), or nations (Sawyer 1967). We suggest that sociologists would gain by dispensing with the notion that the effects of population size are "obvious." Rather, the scope and explanatory power of sociological theories could be greatly enhanced by including size in an explicit fashion.

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