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The American Journal of Sociology, Vol. 89, No. 4 (Jan., 1984), 775-811.

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The Social Structure of a National Securities Market¹

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In this article, a national securities market—the stock options market—is characterized as a social structure represented by the networks of actors who traded options on the floor of a major securities exchange. Trading among actors exhibited distinct social structural patterns that dramatically affected the direction and magnitude of option price volatility. The argument that this market is socially structured is constructed in four parts: behavioral assumptions about the nature of economic actors, models of micronetworks, models of macronetworks, and price consequences. In the ideal-typical model of the market, actors are assumed to be hyperrational and never to act opportunistically. With these behavioral assumptions, the micronetworks of actors should be *expansive*, a condition which would result in undifferentiated and homogeneous macronetworks. Such macronetworks would tend to reduce the volatility of option prices. But in the empirical market studied here, actors are subject to bounded rationality and some act opportunistically. Because of these behavioral constraints, actors' micronetworks are *restrictive*. In large markets, restrictive micronetworks generate well-differentiated macronetworks; both large size and differentiation impede communication among actors, a fact which results in exacerbated option price volatility. In small markets, restrictive micronetworks generate less differentiated market structures. Both small size and less differentiated markets are conducive to efficient communication which results in dampened option price volatility. The findings are discussed in relation to some major premises in microeconomic theory, and some consequent implications for public policy are presented.

The market is one of the preeminent institutions of modern capitalist societies. It is not only the predominant mode of economic exchange but

¹ I acknowledge gratefully the helpful comments, suggestions, and ideas provided by James Burk, Allan Schnaiberg, Harrison C. White, and Christopher Winship on earlier drafts of this paper. The paper benefited especially from the insightful, detailed, and constructive comments of the two anonymous reviewers. The section on price consequences was presented as a paper at the 1982 annual meeting of the American Sociological Association in San Francisco. Mark Granovetter and Peter Marsden provided some very useful comments on that paper which were incorporated in the present one. Requests for reprints should be sent to Wayne E. Baker, The Synectics Group, 1130 Seventeenth Street, NW, Washington, D.C. 20036.

also a major mechanism of social integration. Surprisingly, the market has rarely been the object of direct analytic inquiry in mainstream economics (Barber 1977). Furthermore, the market has received only sporadic attention in sociology (e.g., Weber 1947; Parsons and Smelser 1956). However, sociologists have begun recently to focus their attention on markets, analyzing them as concrete social structures (e.g., White 1981*a*, 1981*b*; 1984; Faulkner 1983). This article continues this renewed sociological interest in markets by analyzing the social structure of a major market in capitalist society: the stock options market.

The history of sociological interest in securities markets, and their kindred commodity futures markets, runs the same course as the general history of sociological interest in markets. Although the securities and futures markets have not been ignored (Rose 1951, 1966; Glick 1957), only recently have a number of sociologists begun to scrutinize closely the structure and operations of these markets. For example, Adler and Adler (1980) have analyzed the stock market from a social psychological perspective; Burk (1982) conducted an institutional analysis of the American stock market; and I have focused on the stock options market, presented here and elsewhere (Baker 1981, 1982, in press). Similarly, Abolafia (1982, in press) and I have analyzed various characteristics of the contemporary futures markets (Baker 1976, 1983). The best indicator of the resurgence of sociological interest in the securities and futures markets is a forthcoming collection of essays on the social dynamics of financial markets (Adler and Adler, in press).

Even though these studies approach securities and futures markets from various sociological perspectives, their common theme is that markets may be viewed as social rather than exclusively economic structures. Not only are these markets characterized more realistically as social structures, but conceptualizing them as social phenomena implies that the full range of sociological research methods, qualitative and quantitative, may be used to study them.

In this study, I have conceptualized the structure of the stock options market as a social network of buyers and sellers and have examined the patterns of trading that occur among participants on the floor of a major securities exchange ("Exchange"). At the Exchange, trading is organized so that options on a particular underlying stock (or small set of stocks) are traded at a unique location on the floor. Each location is thus the observable marketplace for specific options. The aggregates of buyers and sellers who trade in these marketplaces are called "crowds." Two such crowds, one large and one small, were selected for network analysis. The patterns of networks within each crowd, as well as the effects of these networks on the prices of stock options, were analyzed over several periods of trading. Contrary to the expectations of conventional economic

and financial research, this market exhibited discernible social structural patterns with demonstrable effects on the determination of prices. The findings are presented here in the context of a theoretical explanation of the social processes that produced the observed market structures and their outcomes.

The theoretical argument is elaborated in Section I. The research design is presented in Section II. Findings are presented in Section III. Discussion and conclusions are presented in Section IV.

I. THEORETICAL FRAMEWORK

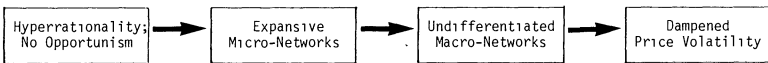
The argument that the stock options market is socially structured is constructed in four parts: behavioral postulates of the market, models of micronetworks, models of macronetworks, and consequences of network structure. Behavioral postulates refers to basic assumptions about the nature of market actors. Micronetworks refers to the structure of ego-centric linkages—networks from the perspective of the individual actor. Macronetworks refers to the overall structure of the market that emerges from micronetwork formations. Finally, consequences refers to the effects of market networks on price determination. (The relationships of these four components are presented schematically in fig. 1.)

The perfectly competitive market is a theoretical model of how actors should behave and how markets should operate. Although it has long been recognized that many empirical markets depart radically from this theoretical model, it remains fundamental to mainstream economic theory (e.g., Malinvaud 1972; Debreu and Scarf 1963). Because this model

(1) General Model:



(2) Ideal-Typical Model:



(3) Empirical Model:

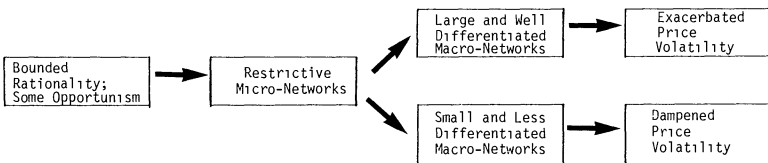


FIG. 1.—Models of markets as networks

refers to how markets should work, it is an ideal-type. Throughout this paper I compare and contrast how the options market should operate as an ideal-type with how it actually operates.

Behavioral Postulates of the Market

In the ideal-typical model of the market, actors are assumed to be hyper-rational; each actor is a self-interested maximizer endowed with unlimited information-processing and analytical faculties. In contrast with these assumptions, I submit that market actors may be described more realistically by two behavioral assumptions made explicit in the "transaction cost approach" to the study of economic organization: "(1) the recognition that human agents are subject to bounded rationality and (2) the assumption that at least some agents are given to opportunism" (Williamson 1981, p. 553).

Bounded rationality emphasizes the inherent limitations of human cognitive powers and capacities to transmit and assimilate information, analyze data, and make decisions under the conditions of complexity and uncertainty (e.g., Williamson 1975, 1979*a*, 1979*b*, 1981; Simon 1978, 1982; Thompson 1967). Opportunism refers to the observation that some actors are not entirely trustworthy and honest; in any given economic situation, at least some actors will take advantage of others, provide false or misleading information, break agreements, and so forth. The purely self-interested maximizer, in contrast, is presumed to be trustworthy and to follow and abide by the rules of the game. As Williamson (1981, p. 554) puts it, "Whereas economic man engages in simple self-interest seeking, opportunism makes provision for self-interest seeking with guile."

The two postulates of bounded rationality and opportunism fit well the options market observed in this study (as well as the securities and futures markets studied by the sociologists cited above).² Floor participants (brokers and market makers, defined below) are acutely aware of their limitations in receiving, processing, and responding to market information. For instance, noise and the physical separation of potential trading partners are often cited as major impediments to the efficient communication

² Although I begin with the same two behavioral postulates as does the transaction cost approach, my focus on the implications of these postulates for the internal organization of the options market differs substantially from the three main foci of the transaction cost approach—the overall structure of the enterprise, the choice between which activities should be performed within the firm and which outside it (i.e., hierarchies vs. markets), and the organization of human assets (Williamson 1981, p. 549). The internal structure of markets, especially competitive and "atomistic" ones such as the options market, has not been examined. Given the difference in focus, both my use of the concepts of bounded rationality and opportunism and their structural implications depart from Williamson's arguments. For example, I argue that bounded rationality and uncertainty in the market lead to opportunism (see also Leblebici and Salancik 1982).

of offers to buy and sell. Furthermore, in an active and fast-moving market, a floor participant is not able to survey fully all potential partners to a trade. Searching for all the alternatives is a costly process (Simon 1978, p. 10). A broker cannot take the time fully to search the “other side” of the market to obtain the best possible price for a customer. Executing an order, therefore, invokes satisficing (taking the first good response to an offer) rather than maximizing behavior.

Opportunism in the market can take many forms, some more insidious than others. Trading with friends, to use a minor example, is a form of opportunism because it bases partner selection at least partially on idiosyncratic and particularistic (i.e., noneconomic) criteria, thereby excluding those who do not share this personal tie. Graver examples are “trading abuses”—behaviors proscribed by Exchange and federal rules—that typically involve fraud, market manipulation, or the misuse of insider information. The language of the market is replete with many colorful terms to describe trading abuses: fictitious trading, chumming, capping, pegging, and so on (U.S. Securities and Exchange Commission [SEC] 1978, pp. 169–89; also Commodity Futures Trading Commission [CFTC] 1982). But a catalog of abuses is unnecessary here; the main point is that opportunism in the market is a widely recognized phenomenon.

Uncertainty in the market.—Uncertainty is an intrinsic part of the market. Because the futures market is designed to approximate a perfectly competitive market ideal, Glick (1957) argues, it naturally creates an environment of extreme uncertainty for brokers and traders. Although trading can be lucrative, there is no guarantee of profits. For instance, in 1977, fully 40% of the 1,153 registered broker-dealers who reported market-making activities on national securities Exchanges reported losses (U.S. SEC 1978, p. 129). Generally, any transaction with a long-term contractual provision (such as futures and options) produces uncertainty about the “future value” of a transaction (Leblebici and Salancik 1982, pp. 229–31). Since the buyer and seller of an option have contrary expectations about the future value of the option, it will always be in the interest of one or the other party to alter or break the agreement.

The volatility of prices itself is a major source of uncertainty, as Leblebici and Salancik (1982) have argued, since it makes the future value of transactions unpredictable. To cope with the uncertainty engendered by price volatility, actors must limit or restrain their trading, and some actors will act opportunistically on occasion. In addition, market actors develop and use many informal “coping mechanisms” to help alleviate the anxiety aroused by uncertainty about price movements (Glick 1957; Baker 1976).

Another source of uncertainty is the formal obligations of a market maker. Market makers must trade for their own accounts to maintain

fair and orderly markets (their “affirmative obligations”) and they must avoid trading that would be inconsistent with this objective (U.S. SEC 1978, p. 131). In order to fulfill these affirmative obligations, a market maker, on the demand of another member of the crowd, must quote the prices at which he or she is willing to buy an option (“bid”) and sell an option (“ask”) and must trade at least one contract at a quoted price. Responding to such demands often means that market makers must trade against their own positions. Even if they anticipate correctly the future value of an option, their affirmative obligations may yet force them to incur losses. Thus, it may be assumed that shirking their affirmative obligations will always be in the interest of at least some market makers. In the language of options trading, some market makers will attempt to limit their “participation” (i.e., to ignore some demands for making markets, thereby reducing the number of undesirable trades they make).

Stock price volatility and crowd size.—While price volatility generates uncertainty about the future value of transactions, it simultaneously creates opportunities for profit making. Consider a simple example: if the price of a stock shows little historical fluctuation, there will be little uncertainty about its future value, but there will also be little potential for making profits. Widely fluctuating prices, in contrast, generate a great deal of uncertainty but also many opportunities to make profits (or suffer losses). Good profit-making opportunities will always attract profit seekers. And, in the options market, actors are formally free to trade in any marketplace, and no limits are set on the size of a crowd. Therefore, the options marketplace with greater price volatility should attract more traders and be much larger than the marketplace with lower price volatility.³

Crowd size determines the potential number of trading relationships available to participants. Furthermore, as the number of actors increases, the number of potential relationships increases even faster (Hare 1962, pp. 228–30). As Mayhew and Levinger (1976, p. 107) put it, “The interaction potential in a human aggregate is a multiplicatively increasing function of aggregate size.” Therefore, a large crowd presents many more

³ Leblebici and Salancik (1982) use the volatility of futures prices, rather than the volatility of underlying cash market prices, to operationalize uncertainty. In the present analysis, I use the volatility of the underlying market prices (stock prices) rather than the volatility of the derivative market prices (stock option prices) for two reasons. First, the volatility of stock prices is not determined by options market floor participants and thus may be treated as an exogenous “input” to the options market. This avoids any potential problems of tautology, such as having actors create the uncertainty/profit-making opportunities that attract them to the market. Second, this allows option price volatility to be treated as an “output” or consequence of options trading; thus, it permits an evaluation of the effects of trading networks on prices. I assume that option price volatility does not affect stock price volatility. While there is some evidence that options trading reduces the weekly volatility of stock prices (Hayes and Tennenbaum 1979), it is reasonable to assume that such feedback does not occur in the short (two-hour) time intervals used here.

potential relationships to market actors than a small crowd. If rationality were not bounded, an actor in a large crowd would be able to take advantage of the many trading relationships available. But numerous actors generate a great deal of noise which interferes with communication. And, as small-group research has found, noise has a detrimental effect on group performance, especially when accurate communication of information is required (Hare 1976, pp. 272–73). In addition, the sheer physical dimensions of a crowd made up of many actors increase the distances between all potential trading partners. Consequently, actors are not able to expand their trading circles significantly, even though many more trading relationships are available. Whether an actor trades in a small crowd or a large crowd, the actor's circle of trading (e.g., number of relationships engaged in) will not differ markedly.

The expectation that actors' trading circles will not differ substantially in small and large crowds runs counter to Mayhew and Levinger's (1976) thesis that, by chance alone, increases in aggregate size should result in increases in the number of contacts per actor. However, they recognize that other factors than size alone influence interaction (Mayhew and Levinger 1976, pp. 93–94; Durkheim 1893). For example, their model is less applicable the larger the distance between actors and more applicable the higher the level of contact technology (also Hawley 1971). In options marketplaces, both large size and growth increase distance; furthermore, the level of contact technology is the same in all crowds. In large (or growing) crowds, the increased probability of interaction is offset by increased distances in a context of unchanging contact technology. Consequently, the trading circles of actors in small and large crowds are quite similar.

Opportunism and social control.—By operationalizing uncertainty as price volatility, Leblebici and Salancik (1982) have shown that opportunism varies with the level of uncertainty in the market. The more volatile a market, the greater the uncertainty; the greater the uncertainty, the more incentive to act opportunistically. Therefore, the more volatile a market is, the more market makers will attempt to avoid their affirmative obligations by ignoring demands for making markets and will thereby lower the number of relationships they form.

Avoiding affirmative obligations, however, can incur negative sanctions. Affirmative obligations were established by Exchanges to guarantee a certain level of market liquidity, depth, and competition. Formal sanctions, such as reprimands, fines, and suspensions, can be applied to offenders. Formal controls, however, are usually last resorts and are applied only in cases of flagrant and recurrent opportunism. Informal controls reportedly work much more effectively to ensure that market makers do not decrease their participation. For, while it may be in an actor's interest

to decrease participation, it is in the interest of others to ensure that all market makers participate so that the financial risks and burden of market making will be shared. As one market maker put it, "We had a new guy in our crowd. He would just trade what he wanted and then hang back. The rest of us were buying all the time as the market went down, and we were selling as the market went up. You can't just take the plums—you have to participate. You have to be willing to buy when the market is going down, buy all the way down, not just here and there. . . ."

Several different informal controls were reported, as I have detailed elsewhere (Baker, in press). Here I report briefly one principal control mechanism. As a floor broker stated, "I would only trade with those market makers who fulfilled that requirement [i.e., high participation]. No matter how deep in the market they were, they would always make markets. I traded with those who added to the liquidity—and the validity—of the market. I know that others will be 'first'—they just wait for the one trade they want—but I won't trade with them." The first person to respond orally to an offer (the "first") is formally entitled to the entire volume offered or any part thereof. Although others may desire to make the trade, they cannot preempt the person who responds first. The potential for social control is obvious. The formal "first" rule is used to exclude any person with whom one does not wish to trade. The broker quoted above used the first rule to exclude market makers who failed to participate fully—he simply never heard the opportunist as the first to respond. In response to such trading ostracism, market makers either increase participation or move on to another crowd. Although it is difficult to state quantitatively the extent to which such informal controls are actually used, their widespread use and effectiveness in maintaining market-maker participation were reported in all interviews. Moreover, the network data are consistent with field observations and reports of informal control of participation.

Participants reported that they were better able to elicit high participation from market makers in small crowds than in large crowds. In small crowds, the relative ease of communication and high visibility of actors' behaviors made it easy to spot opportunists and apply sanctions. In large crowds, where actors are more anonymous and communication is impaired, opportunism can go undetected. The twist here is that social controls work less well in the market situation that provides more incentive to act opportunistically. Even though there would be more demand for market-maker participation in a large crowd because of its size, market makers would be able, to some extent, to avoid their affirmative obligations. In general, while functionalist logic would suggest that the *solution* to opportunism (i.e., social control) would be induced by the *need* for social control (i.e., prevalent opportunism in large crowds), large size

interferes with efficient communication and observation of opportunists, allowing opportunism to go largely unabated. In a small crowd, informal control of participation prevents market makers from avoiding their affirmative obligations but, because of a relatively lower demand for participation in a small crowd, would not result in trading circles that would be substantially larger than those observed in the large crowd.

Market Network Models

The two sets of behavioral assumptions—hyperrationality and no opportunism versus bounded rationality and opportunism—carry very different implications for the probable patterns of market networks. These implications may be viewed on two levels: the micronetwork level and the macronetwork level. Furthermore, the consequences of market networks must be considered—the effects of macronetwork structure on prices (see fig. 1).

Models of micronetworks.—The elemental unit in a market is the dyad, the two parties to a trade; correspondingly, the elemental relationship in a market is the link between two actors, formed by trading. The essential question is, How would individual actors form their egocentric networks?

In an ideal-typical market, actors would not be limited in their ability to communicate with all other actors and to search the “other side” fully in order to find the best price. Furthermore, the lack of opportunism would mean that actors’ only motivation would be to find the best price, and market makers would never lower their participation. In this situation, actors’ micronetwork should be *expansive*: on the average, each actor would trade with many other actors, and exchange high volume (number of options contracts) in each trading relationship. Without opportunism and limited capacities, actors would not tend to curtail or restrict trading. Although individual differences might exist, both the average number of relationships in which an actor engages and the average volume exchanged in a relationship should be high.

Under the assumptions of bounded rationality and opportunism, actors would be compelled to limit and restrict their trading. Participants’ limited information-reception and -processing abilities force them to restrict their search for partners to a trade. Furthermore, opportunism results in a reduction in trading as market makers curtail their participation.

One way in which actors restrict their trading is to trade with those in proximity. A veteran market maker described the problems in trading in a large crowd: “Noise, static. The errors increase as an inverse square of the distance between brokers. . . . You trade with people in close proximity to reduce the risk; there’s money at risk. [For example] if a broker makes a certain percentage on a trade, and has an error, it might take

20 trades to make it up." Bounded rationality compels participants to trade with those in proximity. This behavior is consistent with the finding in small-group research that physical proximity increases the probability that communication will occur between people (Hare 1976; Festinger 1950; Festinger, Schacter, and Back 1950; Thibaut 1950).⁴

In response to bounded rationality and opportunism, actors develop *restrictive* micronetworks. This behavior results in a lower average number of relationships per actor, and a lower average volume exchanged per relationship, than it would under ideal-typical conditions. For reasons discussed above, I expect these two micronetwork characteristics to be virtually the same in both large and small crowds.

Models of macronetworks.—In the ideal-typical market, actors' micronetworks are expansive. Given a sufficient number of transactions, expansive micronetworks should produce an undifferentiated overall market network. In particular, there would be no reason for multiple subgroups to form; under ideal-typical conditions, the structure of a macronetwork would be that of a single clique ("clique" is formally defined in Sec. II). Note that crowd size would not be an important determinant of network structure. Whether a crowd was large or small, the overall network would still be a single, dense clique.

In contrast, empirical markets are differentiated structures of roles and relationships (White 1981*a*, 1981*b*; Faulkner 1983). In options markets, size is the key determinant of the extent of market differentiation (i.e., the extent of multiple subgroup formation). The effects of size on market differentiation are similar whether considered statically or dynamically. If the average number of links per actor and the average volume exchanged in a link are held constant, a large crowd should be more differentiated than a small crowd. Similarly, given that micronetworks are constant, as crowd size increases, trading becomes more decentralized, diffused, and fragmentary, thereby increasing structural differentiation. Therefore, a large crowd should exhibit more differentiation (i.e., multiple cliques) than a small crowd, and an increase in crowd size should increase differentiation. (Look ahead to fig. 3 which portrays the empirical macrostructure of two market networks.)

Size is also a critical concept in microeconomic and in organizational theory, as I will demonstrate briefly here.⁵ In microeconomic theory, size is viewed as a key determinant of market structure and performance.

⁴ Actors' tendency to trade with those in proximity suggests that the formation of micronetworks is not random but, instead, systematic. In addition to proximity, there is some qualitative evidence that systematic partner selection may be based on other noneconomic factors: friendship, enmity, sycophancy, and so forth (Glick 1957, Baker 1976).

⁵ Although I argue that group size is an important constraint on trading interactions, small-group research has produced little systematic evidence of the effects of size on social interaction (see reviews by Hare [1976], McGrath and Altman [1966], Thomas and Fink [1963]).

Two major premises of microeconomic theory are (1) a market with a large number of actors is more competitive and more “atomistic” (i.e., less differentiated) than a market with a small number of actors; and (2) as the number of actors increases in a market, the market becomes more competitive and less differentiated (e.g., Malinvaud 1972; Debreu and Scarf 1963).⁶ Were it not for bounded rationality and opportunism, these premises would have been supported by this analysis. However, large size and growth were found to increase market differentiation, reduce competition, and impair market performance. Small size and stable numbers were found to reduce market differentiation, enhance competition, and improve market performance.

In organizational theory, size is considered a prime generator of structural differentiation (e.g., Mayhew et al. 1972; Blau 1970). Blau (1970, p. 203) argues that increasing organizational size generates differentiation. For example, formal organizations cope with large size by subdividing responsibilities. But unlike Blau’s explanation of differentiation as a rational adaptation to large size, my argument is that a market differentiates because large size and growth outstrip the capacity of actors to communicate efficiently. In Blau’s model, communication and coordination problems are recognized, but they “feedback” and act to attenuate the rate of differentiation before the system malfunctions. But an empirical market has no such built-in limits or constraints on size, and it may expand virtually unabated, exceeding communication capacities and impairing performance.⁷

Mayhew et al. (1972) argue that, by chance alone, size can be expected to induce structural differentiation. The hypothesized relationship of market size and differentiation is consistent with the Mayhew et al. model. However, they only posit an association between size and differentiation. My argument specifies the causal relationships of stock price volatility, size, differentiation, and consequences under the assumptions of bounded rationality and opportunism. Although by chance alone size may be ex-

⁶ In economics, “market structure” is usually not defined in explicitly relational terms. For example, in the field of industrial organization, where “market structure” is an important concept and object of inquiry, structure is operationalized as the number of buyers and sellers, product differentiation, barriers to entry, market share, etc. (Scherer 1980; Shepherd 1972). Similarly, a perfectly competitive market is typically described as “atomistic” (e.g., Malinvaud 1972, p. 164), but how this image translates into the structure of relationships is not addressed. Given this lack of a relational definition, I have interpreted the image of “atomistic” to mean structurally undifferentiated; in network terms, this is the homogeneous form of a single, dense clique of market actors.

⁷ There are some outside limits to the size of the market. For example, the number of actors on the floor of a securities Exchange is finite. Examining the movements of all actors among all marketplaces would reveal that the securities Exchange is a closed system: an increase in the size of one crowd would be reflected in a decrease of equal size of another crowd. But, if only two marketplaces are examined, each may be viewed as an open system with no limits on size.

pected to generate differentiation, in the market situation studied here differentiation is shown to be a result of specific social processes.

Price consequences.—Price has many different characteristics. As White (1981a) emphasizes, the average of prices, such as that implied by the cliché of supply equals demand, is of most interest to economists; but to sociostructuralists, the dispersion or variance of prices is of more concern. In this analysis, I focus on the dispersion of prices, specifically price volatility (formally defined in Sec. II). Two volatilities are of interest: underlying stock price volatility and option price volatility. One analytic advantage of examining the options market is that it is a *derivative* market—its prices are based on prices of the underlying stock. By controlling for the volatility of underlying stock prices, it is possible to assess the effects of network structure on option price volatility. In the model presented here, stock price volatility is viewed as an exogenous variable, an input to options trading; option price volatility is viewed as a consequence or output of options trading.

The single, very dense clique generated under ideal-typical conditions would represent high competition in the market. Without the constraints of bounded rationality and opportunism, market makers would be aware of all offers and would be able to compete aggressively in forming their individual bid-ask spreads. Such aggressive competition would cause their bid-ask spreads to narrow and converge, which would decrease the volatility of executed prices. In short, ideal-typical macronetworks would dampen the volatility of option prices. Framed in terms of market performance, such a dampening effect would improve the orderliness of the options market.

In the empirical marketplaces studied here, size is a critical determinant of option price volatility. In a large market, restrictive micronetworks result in a decline in the pervasiveness of communication among all actors in the market. Growth affects the pervasiveness of communication similarly; as a market grows, actors are increasingly unable to communicate with one another. The decline in the pervasiveness of communication, induced by large size and growth, causes market makers' bid-ask spreads to widen and diverge, resulting in an increase in option price volatility. This process would impair options market performance by decreasing the orderliness of the market.

The detrimental effects of large size on communication and the resulting influence on price volatility were described clearly by a veteran market maker: "In the really large crowds that are really active, it's possible to get trading in very different prices. [Why?] It's noisy; you can't hear. It happens when the stock is changing. Some people trade, and they tell others, and then lots of people are coming over. There are some aberrations sometimes." As might be expected, the participants themselves

are aware of the communication problems created by crowds made up of numerous market actors.

Past a certain point, size induces the formation of multiple cliques. This differentiation exacerbates the communication problems already created by size alone and adds to the increase in option price volatility. While fragmentation contributes to volatile prices, it is important to note that large size (and growth) is the main cause of heightened price volatility. Even if a market does not grow large enough to induce fragmentation, a large market would still tend to produce volatile prices.

Small size should not increase price volatility; in fact, smallness is conducive to a decrease in the volatility of prices. Although actors in a small market are still subject to bounded rationality, each actor is confronted with fewer actors with whom to communicate, compared with the numbers confronting each actor in a large crowd. They are able to make contact with a relatively high percentage of actors and consequently are quite aware of the offers available in the crowd. With such information, actors can compete aggressively in forming their bid-ask spreads. Such aggressive competition would cause actors' bid-ask spreads to narrow and converge, resulting in a decrease in the volatility of option prices. A substantial decrease in the volatility of option prices would increase the orderliness of the market, indicating improvement in market performance.

The effects of macronetworks on option price volatility are analyzed using formal path models. The general theoretical model that guides this analysis is presented in figure 2. As shown, stock price volatility is expected to have direct effects on option price volatility. Macronetwork structure (represented by selected variables) acts as an intervening factor between stock price volatility and option price volatility. The two principal variables used to represent macronetworks are size, the key variable in this analysis, and a measure of the density of interaction in cliques. (Operational definitions of these two are presented in Sec. II.)

II. RESEARCH DESIGN

Research Setting

A single national securities exchange ("Exchange") was selected for this study. This Exchange, like others, is involved in the purchase and sale of stock options. Stock is the proportionate share of ownership held by a stockholder, represented by shares in the form of stock certificates. Stock options are contingent claims to purchase stock ("call options") and to sell stock ("put options"). Only calls were traded in the markets analyzed in this study.

Options are grouped into classes. A class includes all options traded on a particular underlying stock. For example, all options to buy or sell stock in ABC corporation are grouped into a single class of options. Options in each class represent several combinations of expiration months and striking prices (also called exercise prices). The expiration month specifies the last month in which an option may be exercised; the striking price specifies the fixed price at which the underlying stock is either bought or sold. Options are usually written for blocks of 100 shares and issued for periods of less than one year (Gastineau 1979).

Many different classes of options were traded at this Exchange. Trade in each class (or small set of classes) takes place at an assigned location on the floor of the Exchange, representing the physical marketplace for each class. The trading of options outside their designated locale is not permitted. Thus, each marketplace for a class of options may be analyzed as a relatively self-contained and bounded market.

Trading activities in the Exchange's marketplaces share several features:

1. Aggregates of buyers and sellers: In each marketplace, all buyers and sellers form a social aggregate of people who stand together at the appropriate locale. Such an aggregate is labeled, socially, a "crowd." Since all participants are formally free to trade in any marketplace, an aggregate (crowd) is defined as the collection of all persons who traded in a particular marketplace during a specified period of time.

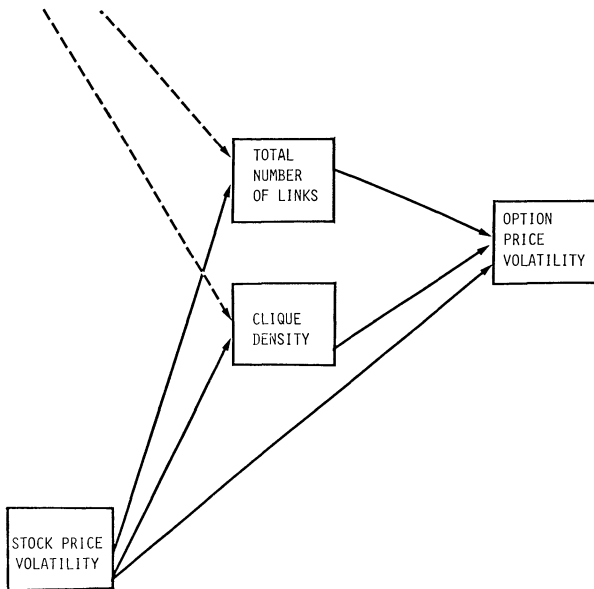


FIG. 2.—General theoretical path model

2. Two formal roles: Each actor may trade in only one of two roles, broker or market maker. A broker buys and sells for other people; a broker is not permitted to buy and sell for his or her own account. A market maker is a professional speculator, trading for his own account; a market maker is not permitted to act as a broker. The market maker's obligations are described above. (Market makers are also called "traders.")

3. Face-to-face interaction: All buyers and sellers interact face-to-face; trading is characterized by close proximity.

4. Open-outcry. All participants must communicate publicly and orally their desires and intentions to buy and sell. These marketplaces are auction-type markets.

Crowds exhibit markedly different patterns of buying and selling. Through fieldwork, I observed two modal types of crowds/marketplaces: high-volume marketplaces in which large crowds traded, and low-volume marketplaces in which small crowds traded. To maximize the potential for discovering different structures of trading, one crowd from each type was selected for analysis. The first crowd, a large collection of participants, traded a very active class of options. The second crowd, a relatively small collection of participants, traded three moderately active option classes. These aggregates and their networks are referred to as ABC and XYZ, respectively.

Research Methods and Data

Multiple methods were used to study the options market. The initial stage of research involved exploratory fieldwork, primarily participant observation, and informal interviewing at the Exchange over a 10-week period. The second stage involved analyses of the networks of participants in each of the two crowds in order to model the structure of trading relationships. Details of the network analysis are presented below. In the third stage, key participants who traded in the networks were interviewed to elicit their perceptions and explanations of the market structures discovered through network analysis. These interviews provided information on the social dynamics behind the observed network configurations.

Network methods.—From a social network perspective, an options market may be defined as a specific set of trading relationships, represented by linkages formed by transactions in a particular class (or small set of classes) of options, among a defined set of brokers and market makers. A link is a recorded transaction between two actors. When multiple transactions occur between the same two actors, the trades are interpreted as one link, representative of a single trading relationship. The strength of a relationship is represented by the total volume exchanged in the relationship.

The basis of links and their strengths is the set of extant trades of the options traded in ABC and XYZ marketplaces. These data, forming the raw data for the networks, are the trades recorded by the Exchange.⁸ As a trade occurs in the crowd, the option writer (seller) writes all pertinent information on a card and hands it to a computer terminal operator who enters the information in the Exchange's computer. Each entry contains several bits of information: date and time of the trade, option traded, volume, premium (option price), buyer's ID code, seller's ID code, and the current price of the underlying stock. As originally entered, IDs were the participants' identifying acronyms, unique codes assigned to each broker and market maker. To ensure the anonymity of the individuals, the Exchange masked the original acronyms by replacing each unique ID with a unique alternative code.

A network of options trading is determined by the set of transactions that are formed into links and arrayed as a set of relationships. Since options are traded continuously throughout each day, the stream of transactions was segmented into discrete sets of transactions. Veteran traders interviewed in the first stage of research noted that the typical day is divided naturally into three distinct periods, each characterized by a distinct pattern of trading. Their perceptions were corroborated by field-work observations. Therefore, each day was divided into three two-hour intervals. All trades occurring in a given interval were used to form a single network of trading; each day is represented by three distinct networks.⁹

In some network studies, a single observed network is sufficient to represent underlying structure (e.g., Breiger 1976; Burt 1978). In other studies, several observations of networks (i.e., multiple networks) have been analyzed to model the formation of groups (Doreian 1979/80) and the structure of change in groups (White, Boorman, and Breiger 1976; Galaskiewicz and Wasserman 1981). Since options trading is often capricious, it is necessary to analyze several observations of networks in order to

⁸ Two types of data are generally used for network analysis: cognitive data (i.e., recall of who one talks to) and behavioral data (i.e., who one actually talks to). Data used in this study are behavioral data: actual records of who traded with whom. The use of behavioral data greatly increases the inherent validity of any network analysis. Several network analysts have focused on the accuracy of cognitive data in comparison with behavioral data. They state categorically that, based on their studies of cognitive and behavioral data, cognitive data cannot be used for drawing any valid inferences about behavioral social structure (Bernard and Killworth 1977; Killworth and Bernard 1976, 1979; Bernard, Killworth, and Sailer 1979/80).

⁹ A small percentage of trades (usually 5%–15%) in each period were deleted because of missing data (e.g., either buyer's or seller's IDs or both were missing). Since a single link often comprises multiple trades and the typical participant trades with multiple partners, the deletion of a small percentage of trades omits very few links and participants from the networks.

model the underlying structure of trading relationships. Therefore, 10 days of trading were analyzed, randomly sampled from a month of 20 business days in the late 1970s. All trades in the option classes traded in ABC and XYZ marketplaces within each sampled day were included. Each day of trading was divided into three two-hour intervals, resulting in 30 observations of ABC networks and 30 observations of XYZ networks.

A clique-detection program called NEGOPY (Richards and Rice 1981; Richards 1975) was used for macronetwork analysis. This program searches a network for regions of dense interconnections, grouping well-interconnected nodes into cliques (Richards calls cliques "groups"). A clique is formally defined as a subset of at least three nodes in which each node trades more than 50% of its volume with other nodes in the subset, a direct or indirect path exists from each node to every other node in the subset, and no node is "critical" (a node is critical if its removal from the clique causes the clique to fail to meet the other criteria). There are four types of nonclique nodes. A liaison is a node that connects two or more cliques but is not a member of any clique because it fails to meet the 50% criterion for clique membership. An isolate is a node connected by a single link to another node. A dyad is composed of two nodes connected only to each other. A tree node is found in a subset of nodes with $n - 1$ links (where n = number of nodes). A tree structure often has isolates on both ends and tree nodes between them. (Refer to fig. 3 for graphic representations of options market networks.)

Price volatility and network variables.—In the field of finance, the variance (or standard deviation) is one of the measures typically used to represent price volatility (e.g., Bookstaber 1981; Black and Scholes 1972, 1973). But since the variance is an unstandardized measure of dispersion, it cannot be readily used to compare the relative volatility of two or more distributions. Therefore, Martin and Gray's (1971) measure of relative variability based on the mean absolute deviation from the mean was used to represent stock and option price volatility. The formula for this measure is:

$$V(D\bar{x}) = \frac{\sum |X - \bar{X}| / n}{\bar{X}} \bigg/ 2 \left(1 - \frac{1}{n} \right),$$

where $V(D\bar{x})$ = a standardized measure of relative variability (volatility), X = observed price (weighted), \bar{X} = mean price (weighted), and n = number of observations (weighted). This measure of relative dispersion varies from zero to one and may be stated as a percentage of its maximum (Martin and Gray 1971, p. 497). For the regression analyses, this measure was divided by the number of transactions to express volatility on a per transaction basis.

Size and the density of interaction within cliques are the two variables

used to represent macronetwork structure. Size may be defined in several ways. In microeconomics, size is usually defined as the number of actors in a market. From a social network perspective, however, a relational definition of size, one that reflects the quantity of interactions among actors, is preferable. Thus, I have defined and operationalized size as the total number of buying and selling relationships in a crowd during a period of trading. Note that from a purely technical point of view, either definition of size is appropriate because the number of relationships and

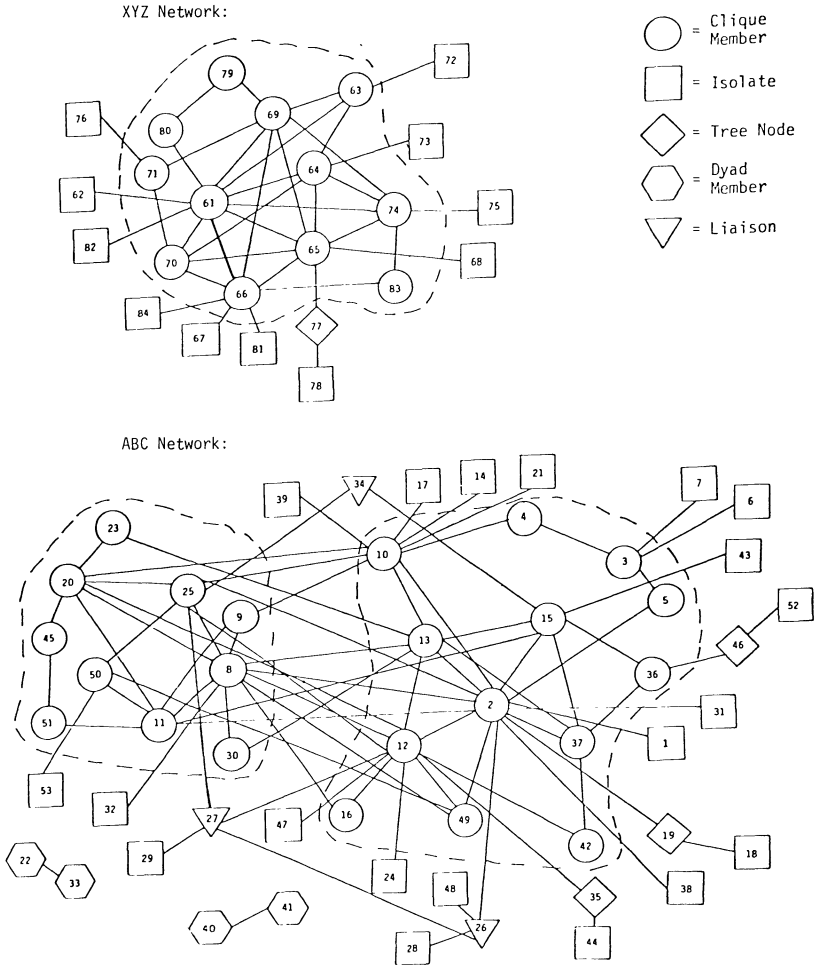


FIG. 3.—Empirical examples of XYZ and ABC market networks (graphic representations of actual networks of trading in XYZ and ABC marketplaces during the same afternoon period).

the number of actors are very highly correlated ($r = .93$ in ABC, $r = .80$ in XYZ). The density of interaction within subgroups is operationalized as “clique density” (the actual number of links within cliques as a percentage of maximum potential links within cliques).

III. FINDINGS

Stock Price Volatility and Crowd Size

Over the 30 periods of trading, the average volatility of ABC stock prices was 2.77%. That is, the prices of ABC stock varied 2.77% of the maximum variability possible. In contrast, the average volatility of the prices of the three stocks underlying XYZ market was substantially lower. Over the 30 periods of trading, their average volatility was only 0.75%. Therefore, the stock prices underlying ABC options market were over 3.5 times as volatile as the stock prices underlying XYZ options market.

Since profit-making opportunities vary directly with stock price volatility, many more actors should be attracted to ABC marketplace than to XYZ marketplace. The data support this hypothesis. While 648 different actors made at least one trade in at least one period of trading in ABC, only 203 different actors made at least one trade in at least one period of trading in XYZ.¹⁰ An average of 70.8 actors traded in ABC marketplace during a period, but an average of only 27.2 actors traded in XYZ marketplace during a period. Similarly, there were marked differences in the average number of trading relationships in a period. In ABC an average of 151.8 links were formed in a period, while in XYZ an average of 63.5 links were formed in a period.

Patterns of Micronetworks

Egocentric patterns.—Under ideal-typical conditions, each ABC actor would trade with every ABC actor, and each XYZ actor would trade with every XYZ actor. While both sets of actors would engage in a maximum number of relationships, the observed differences in size would mean that many more relationships were available to ABC actors than to XYZ actors. Thus, an ABC actor would engage in a higher number of relationships than an XYZ actor. Furthermore, given that the number of potential links is a multiplicative function of size, potential trading volume would, similarly, be a multiplicative function of size. Since large size offers ABC participants the opportunity to trade very high volume,

¹⁰ These figures also indicate that ABC crowd experienced much faster turnover than did XYZ crowd. Not only was ABC much larger than XYZ, but also it was involved in a relatively quicker circulation of actors in and out of the marketplace. These differences in “relative stability” are analyzed elsewhere in detail (Baker 1981).

they would exchange higher volume in each relationship than their XYZ counterparts.

Under the assumptions of bounded rationality and opportunism, ABC and XYZ egocentric networks should be similarly restrictive. In fact, only minor differences exist between ABC and XYZ egocentric networks, analyzed as averages over all periods ($N = 30$). On the average, each ABC participant engaged in 2.12 relationships in a period; similarly, on the average, each XYZ participant engaged in 2.34 relationships in a period. Further, the average volume exchanged in a relationship is virtually the same. There were 5.79 option contracts in each ABC relationship and 5.80 option contracts in each XYZ relationship. Regardless of the trading opportunities available in a crowd, the micronetworks of options market actors are quite similar—a finding in stark contrast with the structure of micronetworks suggested by the economic model of markets.

Diurnal patterns of micronetworks.—The qualitative data indicated that trading patterns varied systematically throughout a typical day. The possibility of diurnal patterns provides an opportunity to test further for differences between ABC and XYZ market networks, as well as to examine the daily processes and dynamics of trading.

Heightened activity in both markets occurs in the morning and afternoon periods; the midday period is typically the slowest and least active of the three periods. This diurnal pattern can be explained by examining the flow of orders to the market. Orders from public and institutional investors build up overnight; the accumulation is released when the market opens in the morning. Speculative activity follows the flow of public orders, accentuating trading activity in the morning period. Trading diminishes during the middle of the day as public, institutional, and consequently speculative activity declines. Trading activity picks up again in the afternoon when participants make the final trades of the day. Both network patterns, as demonstrated below, tend to follow the diurnal flow of orders, but in different ways.

The diurnal patterns of network structure may be stated as a general hypothesis of curvilinearity, expressed formally in three specific interrelated hypotheses:

$$\begin{array}{lll}
 (1) H_0: P_1 = P_2 & (2) H_0: P_2 = P_3 & (3) H_0: P_1 = P_3 \\
 H_1: P_1 > P_2 & H_1: P_2 < P_3 & H_1: P_1 \neq P_3 \\
 \text{where: } P_1 = \text{Period 1; } P_2 = \text{Period 2; } P_3 = \text{Period 3.}
 \end{array}$$

(Note that I do not want to reject the null hypothesis of no difference between P_1 and P_3 [hypothesis 3] in order to support the general hypothesis of curvilinearity.) This set of hypotheses represents a strict definition of

curvilinearity. The strict definition may be relaxed by omitting hypothesis 3.

To test these hypotheses, the means of selected network variables were calculated and differences between means were tested using the *t*-test for paired samples. The *t*-test for paired samples was used because periods were sampled in triplets (trading days were sampled, and all periods within a day were included). Pairing reduces the extraneous influences on the network variables measured; that is, pairing reduces the effects of period-to-period variability. All statistics are reported in table 1.

The number of actors in ABC marketplace reveals a U-shaped curvilinear pattern. Thus, many more potential trading relationships are available in the morning and afternoon periods than in the midday period. Under ideal-typical conditions, these potentialities would be realized in a higher number of links per ABC actor, and higher volume exchanged per link, in the first and third periods than in the second period. In other words, these two measures of egocentric networks also should be curvilinear. However, the average number of links per ABC actor is constant across the three periods of the day; ABC actors do not engage in significantly more relationships even though more potential ones are available. Furthermore, the average volume exchanged in each ABC relationship does not vary significantly across the three periods. The egocentric networks of ABC actors remain constant throughout the day even though the number of actors is curvilinear.

The ABC micronetworks remain constant throughout the day for two main reasons. First, although an increase in the number of actors presents more trading opportunities, bounded rationality prevents actors from engaging in significantly more relationships or increasing the volume exchanged in a relationship. Second, even though an increase in the number of actors increases the demand for market making, ABC market makers are able to ignore some of these demands and thereby hold their participation constant. In ABC, both bounded rationality and opportunism operate to produce micronetworks that do not change substantially throughout the day.

Unlike ABC marketplace, XYZ does not reveal significant differences in the number of actors trading over the three periods. But the number of links per actor is strongly curvilinear: XYZ actors engage in significantly more relationships in the first and third periods than in the second period. Even though the number of potential relationships does not change, XYZ actors expand their trading circles. They do not, however, vary the volume exchanged in a relationship across the three periods.

The expansion of trading circles probably reflects increased market-maker participation during the morning and afternoon periods. In addition, with small size (and therefore less noise and shorter distances),

TABLE 1—PAIRED t -TESTS FOR DIURNAL NETWORK PATTERNS

VARIABLE AND PERIOD	ABC CROWD			XYZ CROWD			
	Mean	SD	Hypothesis	Mean	SD	Hypothesis	Probability
Number participants:*							
P ₁	79.60	21.573	P ₁ > P ₂	27.50	6.916	P ₁ > P ₂	.137
P ₂	61.80	20.996	P ₂ < P ₃	24.90	5.840	P ₂ < P ₃	.172 (N)
P ₃	71.00	13.197	P ₁ ≠ P ₃	29.10	11.396	P ₁ ≠ P ₃	.729
Mean volume per link:*							
P ₁	6.2373	1.299	P ₁ > P ₂	5.6267	1.195	P ₁ > P ₂	.282
P ₂	5.7488	1.381	P ₂ < P ₃	6.0639	1.654	P ₂ < P ₃	.194 (N)
P ₃	5.3966	.879	P ₁ ≠ P ₃	5.7076	1.567	P ₁ ≠ P ₃	.906
Mean links per participant:*							
P ₁	2.1077	.090	P ₁ > P ₂	2.6662	.601	P ₁ > P ₂	.010
P ₂	2.0354	.423	P ₂ < P ₃	1.9829	.395	P ₂ < P ₃	.003 (S)
P ₃	2.2307	.341	P ₁ ≠ P ₃	2.3410	.396	P ₁ ≠ P ₃	.189
Number of cliques:							
P ₁	1.40	.516	P ₁ > P ₂	1.10	.316	P ₁ > P ₂	1.0
P ₂	1.00	.471	P ₂ < P ₃	1.10	.876	P ₂ < P ₃	1.0 (N)
P ₃	1.70	.675	P ₁ ≠ P ₃	1.10	.568	P ₁ ≠ P ₃	1.0
Clique density:							
P ₁1478	.040	P ₁ > P ₂	.2971	.038	P ₁ > P ₂	.066
P ₂1597	.061	P ₂ < P ₃	.2219	.134	P ₂ < P ₃	.067 (W)†
P ₃1419	.015	P ₁ ≠ P ₃	.2859	.122	P ₁ ≠ P ₃	.749
% clique volume:							
P ₁6153	.236	P ₁ > P ₂	.8605	.142	P ₁ > P ₂	.024
P ₂6587	.241	P ₂ < P ₃	.5926	.335	P ₂ < P ₃	.108 (W)
P ₃6430	.154	P ₁ ≠ P ₃	.7155	.268	P ₁ ≠ P ₃	.183
% clique links:							
P ₁5294	.183	P ₁ > P ₂	.6610	.126	P ₁ > P ₂	.040
P ₂5689	.220	P ₂ < P ₃	.4613	.276	P ₂ < P ₃	.162 (W)
P ₃5457	.156	P ₁ ≠ P ₃	.5415	.202	P ₁ ≠ P ₃	.153

NOTE.—(S) = strong support of curvilinear hypothesis ($P < .05$), (W) = weaker support of curvilinear hypothesis (either P₁ > P₂ or P₂ < P₃ is not significant [$P > .05$]), (N) = no support of curvilinear hypothesis.

* In overall network.
† Marginally significant

XYZ participants may be able to communicate efficiently and search the “other side” of the market rather completely. Though still subject to the immutable constraints of bounded rationality, participants may not be pushed beyond their human limits. The fact that XYZ actors do not increase the volume exchanged in a relationship, however, continues to indicate that even XYZ actors must limit their trading in some ways.

The differences in observed diurnal patterns run counter to those expected under ideal-typical conditions. When ABC crowd grows, egocentric networks should also expand—but they remain constant; because XYZ crowd remains stable, egocentric networks should also stay constant—but they expand significantly. Given the more realistic assumptions of bounded rationality and opportunism, the observed diurnal dynamics of ABC and XYZ micronetworks make sense.

Patterns of Macronetworks

Size differences.—The critical macrostructural difference between ABC market and XYZ market is size. As discussed in the second paragraph of Section III, on the average ABC is much larger than XYZ: there are approximately 2.5 times as many relationships in ABC market as in XYZ market. Given that the micronetworks of actors in both markets are similar, the observed difference in size indicates that communication is much less pervasive in ABC than in XYZ. Because ABC is much larger than XYZ, ABC is expected to be much more differentiated than XYZ (see below), resulting in a further breakdown in communication in the larger market. But it is important to reiterate that large size alone is sufficient to impede communication among all actors.

Market differentiation.—In the ideal-typical situation, market actors would interact in ways that would generate an undifferentiated macronetwork: a single, dense clique. If ABC and XYZ were produced under ideal-typical conditions, both would take this form. Given the observed micropatterns, however, each macronetwork is expected to be more or less differentiated.

Theoretically, at least one clique should always form; thus, one clique is the theoretical baseline from which empirical macrostructures can be assessed. Structural differentiation is defined operationally as the occurrence of multiple cliques (two or more) during a given period. Because at least one clique is always expected, evaluating differences in differentiation between empirical markets focuses on the relative frequency with which more than one clique forms in one market compared with another market. The complete absence of cliques should be rare, occurring only when the quantity of interactions is insufficient to support the formation of macrostructures (e.g., as in a thin or very inactive market).

Because ABC and XYZ egocentric networks are very similar, but ABC is much larger than XYZ, I expect that (1) multiple cliques should form more often in ABC than in XYZ, (2) single cliques should form less often in ABC than in XYZ, and (3) the complete absence of cliques should occur less often in ABC than in XYZ. As shown in table 2, the data support these expectations. Most important, multiple cliques formed more than twice as often in ABC than in XYZ. Single cliques formed often in both networks, but they formed less frequently in ABC than in XYZ. Cliques were seldom absent in either network, but as expected, cliques were missing less frequently in ABC than in XYZ. The data also support the assumption that cliques fail to form when the quantity of interactions is low. There were fewer ABC links (41) in the period in which no cliques formed than in any other period of ABC. Similarly, two of the three periods of XYZ in which no cliques formed contained fewer links (21 and 25) than any other period of XYZ. The other period in which no cliques formed contained the fourth lowest number of links (33) of all XYZ periods. (The third lowest period contained 32 links, and one other period contained 33 links; cliques formed in both of these periods.)

For illustration, refer to figure 3, which presents graphically the empirical macrostructure of ABC and XYZ networks during the same period of trading. As shown in the upper panel, during this period XYZ market was composed of a single clique, surrounded by a periphery of isolates. Although this structure reveals some differentiation (i.e., a center-and-periphery structure), it approximates the ideal-typical structure much more closely than does ABC network. As shown in the lower panel, during this period ABC market was fragmented into two cliques, each with its own periphery of isolates. The occurrence of some cross-subgroup trading indicates that the two cliques were not completely separate; but, since a clique represents an arena in which each of its respective members concentrates more than 50% of his volume, ABC market is shown to be divided into two distinct areas of concentrated activity. As such, ABC macrostructure represents a well-differentiated market.

TABLE 2

EXTENT OF STRUCTURAL DIFFERENTIATION IN
ABC AND XYZ NETWORKS ($N = 30$)

NUMBER OF CLIQUES IN A PERIOD	PERCENTAGE OF PERIODS	
	ABC	XYZ
Multiple cliques	36.7	16.7
Single clique	60.0	73.3
No cliques	3.3	10.0
Total	100.0	100.0

Network density and concentration within cliques.—Under ideal-typical conditions, everyone should be able to trade with everyone else, which would result in a single, dense clique. At the extreme, the density of relationships (actual links as a percentage of potential links) in such a network would approach 100%. Although ABC is larger than XYZ, the density of each would be similarly high if these networks were produced under ideal-typical conditions. Even if these networks were not produced under ideal-typical conditions, by chance alone the density of the larger crowd should be higher than the density of the smaller crowd (Mayhew and Levinger 1976). But, given that ABC and XYZ actors engage in approximately the same average number of relationships per actor, the density of ABC is expected to be much lower than the density of XYZ. In fact, the average density of ABC networks is only 6.2%, while the average density of XYZ networks is 17.5%. Trading in the larger crowd is much more diffused and decentralized than it is in the smaller crowd.

In the ideal-typical market, all trading activity would be concentrated within the single clique; all links formed in the network would be formed within the clique, and all volume exchanged in the network would be exchanged within the clique. But since ABC differentiates more often than XYZ, and trading is more decentralized in ABC than in XYZ, lower percentages of links and volume should occur within ABC cliques compared with the percentages of links and volume that should occur within XYZ cliques.

While the average percentage of relationships within cliques is approximately the same in both ABC and XYZ (about 55%), a substantially higher average percentage of total volume is traded within XYZ cliques (76%) than is traded within ABC cliques (64%). Thus, trading is somewhat more heavily concentrated within XYZ cliques than within ABC cliques.

Diurnal patterns of macronetworks.—The macronetworks of ABC and XYZ exhibit diurnal patterns that correspond to the diurnal patterns of their respective micronetworks. First and foremost, given that the number of ABC actors is curvilinear but the number of links per actor is not, ABC macronetworks should be more differentiated in the first and third periods than in the second period. As shown in table 1, only one clique tended to form in the midday, but a significantly higher number of cliques per period formed in the morning and afternoon. Given that the size of XYZ crowd does not vary significantly throughout the day, there should be no differences in the number of cliques per period. As shown in table 1, the average number of XYZ cliques per period is identical across the three periods.

The concentration of trading within ABC cliques did not change throughout the day. Neither the percentage of total volume traded within

cliques nor the percentage of total links formed within cliques varied significantly throughout the day. Also, clique density did not change significantly across the three periods. Although the increase in ABC crowd size in the first and third periods would be expected to increase the concentration of trading within cliques, the concomitant increase in structural differentiation offsets this potential by decentralizing and fragmenting trading.

In contrast, the concentration of trading within XYZ cliques should reveal a U-shaped curvilinear pattern. Since crowd size and the number of cliques remain constant but the number of links per actor is curvilinear, trading should be concentrated more heavily in the first and third periods than in the second period. Such is the case: both the percentage of links formed within cliques and the percentage of volume exchanged within cliques are curvilinear. Also, clique density reveals a curvilinear pattern (though differences in means are marginally significant).

The observed diurnal patterns of ABC and XYZ market networks illuminate some of the basic social processes that underlie these markets. The process of trading in ABC may be characterized as "fragmentation." The networks in ABC frequently exhibit the formation of multiple cliques, distinct subgroups of participants trading in the crowd during a given period. In periods of heightened activity, the morning and afternoon, traders from other crowds migrated to ABC marketplace to trade ABC options. The influx of newcomers increased the size of ABC crowd. But neither the average number of relationships in which each participant engaged nor the average strength of relationships changed in periods of greater activity. This created greater potential for subgroup formation, a potential that was realized empirically in the fragmentation of ABC networks into multiple cliques.

The process of trading in XYZ may be characterized as "intensification." The XYZ networks rarely fragmented; instead, they were usually composed of a single central clique and a periphery of isolates. During periods of heightened activity, XYZ crowd did not experience a substantial immigration of newcomers. Instead, the expansion of activity in XYZ options was fostered and facilitated by the central core of regular participants in XYZ marketplace. Members of this core intensified their trading with each other by increasing the average number of relationships in which they engaged and increasing the concentration of trading within subgroups. Thus, the central clique's intensification accommodated increases in trading activity.

Effects on Option Price Volatility

In the ideal-typical market, macronetworks should act to dampen the volatility of option prices. However, given the observed structure of ABC

networks (large size and fragmentation), I expect that ABC macronetworks will exacerbate the volatility of option prices. With the small size of XYZ macronetworks and the fact that they resemble ideal-typical market structure, I expect that XYZ macronetworks will dampen the volatility of option prices.

The general theoretical path model is presented in figure 2. As discussed above, network structure is represented by two principal variables: the total number of trading relationships (total links) and the density of interaction within cliques (clique density). Since option prices are considered to be derivatives of stock prices (e.g., Gastineau 1979), stock price volatility should be correlated positively with option price volatility in both ABC and XYZ. For ABC, stock price volatility is expected to be correlated positively with total links. As the volatility of underlying stock prices increases, greater profit-making opportunities in ABC options become available which attract newcomers to ABC marketplace. Therefore, crowd size (total links) should be correlated positively with stock price volatility. Crowd size should also be correlated positively with option price volatility. Since clique density is constant in ABC (due to fragmentation in periods of increased size), neither stock price volatility and clique density nor clique density and option price volatility should be associated significantly.

For XYZ, stock price volatility is expected to be correlated positively with clique density. As the volatility of underlying stock prices increases, XYZ actors increase participation and compete more aggressively, causing the central clique to become denser. Clique density should be correlated negatively with option price volatility. Since the volatility of XYZ stock prices is generally low compared with ABC stock prices, an increase in XYZ stock price volatility does not attract enough newcomers to increase significantly the number of actors. (Faced with a choice between trading in ABC or XYZ, profit seekers would choose ABC.) Therefore, total links should not be associated with stock price volatility or with option price volatility.¹¹

The path model for ABC crowd.—The decomposition of effects table for the ABC path model is presented in table 3. As expected, stock price volatility is correlated positively with option price volatility: a 1 standard deviation (SD) increase in stock price volatility increases option price volatility by .454 SD, with the network variables held constant. Total links is correlated positively with option price volatility. When stock price volatility and clique density are controlled, a 1 SD increase in total links increases option price volatility by .471 SD. Stock price volatility also

¹¹ As noted above, three option classes were traded in XYZ marketplace. To avoid any potential for confounding influences, the analysis of price volatility focused on the most active of the three classes. Over 60% of the total volume of options traded in XYZ belonged to this option class.

has moderately strong indirect effects on option price volatility, almost exclusively through total links instead of through clique density. Furthermore, clique density is not correlated significantly with either price variable, as expected, and may be dropped from the model.

The regression equation for this model of ABC is $\hat{Y} = .471 (TL) + .454 (SV)$, where TL = total links measured in SD units, SV = stock price volatility measured in SD units, and \hat{Y} = predicted option price volatility in SD units.

This model explains about 66% (adjusted R^2) of the total variation of option price volatility. That is, two-thirds of the total variation of the volatility of option prices can be explained by the volatility of stock prices and the total number of relationships in the crowd.

The path model for XYZ crowd.—The decomposition of effects table for the XYZ path model is presented in table 4. As expected, stock price volatility is correlated positively with option price volatility: a 1 SD increase in stock price volatility increases option price volatility by .423 SD, with the network variables held constant. Clique density has a strong direct effect on option price volatility. When stock price volatility and

TABLE 3
DECOMPOSITION TABLE FOR ABC PATH MODEL

BIVARIATE RELATION	TOTAL CORRELATION	CAUSAL			NONCAUSAL
		Direct	Indirect	Total	
Stock/links629*	.629*	None	.629	None
Stock/density095	.095	None	.095	None
Stock/option746*	.454*	.292	.746	None
Links/option756*	.471*	None	.471	.285
Density/option016	-.033	None	-.033	.049
Links/density014	None	None	None	.014

* $P < .001$.

TABLE 4
DECOMPOSITION TABLE FOR XYZ PATH MODEL

BIVARIATE RELATION	TOTAL CORRELATION	CAUSAL			NONCAUSAL
		Direct	Indirect	Total	
Stock/links	-.219	-.219	None	-.219	None
Stock/density007	.007	None	.007	None
Stock/option424*	.423*	.001	.424	None
Links/option	-.309	-.019	.004	-.015	-.294
Density/option	-.573*	-.569*	None	-.569	-.004
Links/density346	None	None	None	.346

* $P < .001$

total links are controlled, a 1 SD increase in clique density decreases option price volatility by .569 SD. Stock price volatility has virtually no effect on clique density; the trading behavior of XYZ clique members does not respond to changes in volatility. As a result, the indirect effect of stock price volatility on option price volatility through clique density is quite weak. The total links variable is not associated significantly with either price variable and thus may be dropped from the model.

The regression equation for this model of XYZ is $\hat{Y} = -.576(CD) + .428(SV)$, where CD = clique density measured in SD units, SV = stock price volatility measured in SD units, and \hat{Y} = predicted option price volatility measured in SD units.

This model explains about 47% (adjusted R^2) of the total variation of option price volatility. That is, almost half of the total variation in option price volatility can be explained by the volatility of stock prices and the density of relationships within cliques. (Less of the total variation of the dependent variable is explained in this model than in the previous model owing to the lack of major indirect effects of stock price volatility on option price volatility.)

In sum, ABC and XYZ macronetworks influence option price volatility in opposite ways. In ABC, as the total number of relationships increases, so does the volatility of ABC option prices, when the volatility of underlying stock prices is controlled. In other words, an increase in the size of ABC market increases the volatility of option prices above and beyond that expected by the volatility of stock prices alone—an exacerbating effect. In XYZ, as the density of relationships within cliques increases, the volatility of option prices decreases, when the volatility of underlying stock prices is controlled. That is, the intensification of trading within cliques decreases the volatility of option prices below that expected by the volatility of stock prices alone—a dampening effect.

IV. DISCUSSION AND CONCLUSIONS

The findings support the argument that the stock options market is socially structured. Both options marketplaces exhibited substantial social structural patterns that dramatically influenced the direction and the magnitude of price volatility. In addition, the differences in structure between the two empirical markets run counter to some of the fundamental premises of microeconomic theory. Microeconomic theory asserts that ABC market should be more competitive than XYZ market since a larger number of competitors (participants) trade in ABC marketplace. If ABC were more competitive than XYZ, it would exhibit less differentiation than would XYZ. But the opposite is true: ABC, the larger market, exhibits greater structural differentiation than does XYZ, the smaller

market. The ABC market is, in fact, less competitive than XYZ because large size and differentiation impede the efficient flow of information among all market actors.

Microeconomic theory also presumes that a market becomes more competitive, and hence less differentiated, as the number of actors increases. But whenever ABC market grew in size (usually in the first and third periods), the market exhibited greater—not lesser—differentiation. Market growth was found to impair the competitiveness of ABC market. Conversely, in a manner quite paradoxical to microeconomic theory, stable size (XYZ) was found to be conducive to heightened competitiveness.

Microeconomic theory argues that there is no rationale for trading in subgroups in a competitive market. According to this logic, ABC participants are not economically rational when they form multiple cliques because trading in cliques should not enable actors to achieve greater profits than they could by behaving competitively (i.e., by not forming cliques). But this premise is predicated on both the assumption of hyper-rationality and the belief that ABC actors form multiple cliques intentionally. In reality, both bounded rationality and opportunism compel actors to restrict and curtail their trading. One of the results of the curtailment of trading in large crowds is the formation of multiple subgroups. These subgroups are truly emergent—they are the unintended outcomes of human limitations on trading in the context of large aggregates.

The discovery that the options market is socially structured would be interesting but not as important if the structure of the market did not influence price determination. Implicit in much research on the options market is the assumption that trading networks do not substantially affect the volatility of prices. However, as the path analyses of price consequences demonstrate, empirical macronetworks substantially influence option price volatility.

Price volatility is related to the relatively abstract economic concept of “market orderliness.” Usually, market orderliness is defined arbitrarily as low price volatility and disorderliness as high price volatility, although either low or high volatility may be appropriate for actual market conditions (Burns 1979; Logue 1975). But, as the findings show, orderliness is a relative matter. A market may be considered to be relatively orderly if social networks act to dampen price volatility and relatively disorderly if social networks act to exacerbate price volatility.

The findings may be summarized as “the paradox of large numbers.” While under ideal-typical conditions large numbers and growth create a competitive and minimally differentiated market, the opposite occurs in actual market situations. This paradox cannot be explained adequately by conventional microeconomic theory. But the sociological model of markets-as-networks presented here offers a better explanation of the

observed patterns of ABC and XYZ markets and their effects on price volatility.

Given the observed constancy of micronetworks, the main determinant of market structure is size. In XYZ, the market rarely expanded to the point at which fragmentation would occur; in ABC, the market often grew large enough to induce fragmentation. This implies that there may be a threshold for market size below which fragmentation is less likely to occur and above which fragmentation is more likely to occur. From the monopoly (or monopsony) situation up to this threshold, an increase in size would tend to improve market performance. Beyond this threshold, an increase in size would tend to impair market performance. In short, the relationship between market size and performance is not linear, as assumed in microeconomics; rather, it is curvilinear. This relationship is depicted in figure 4.

As shown on the curve in figure 4, ABC is located beyond the threshold and XYZ is located near the threshold. The other labeled sections of the

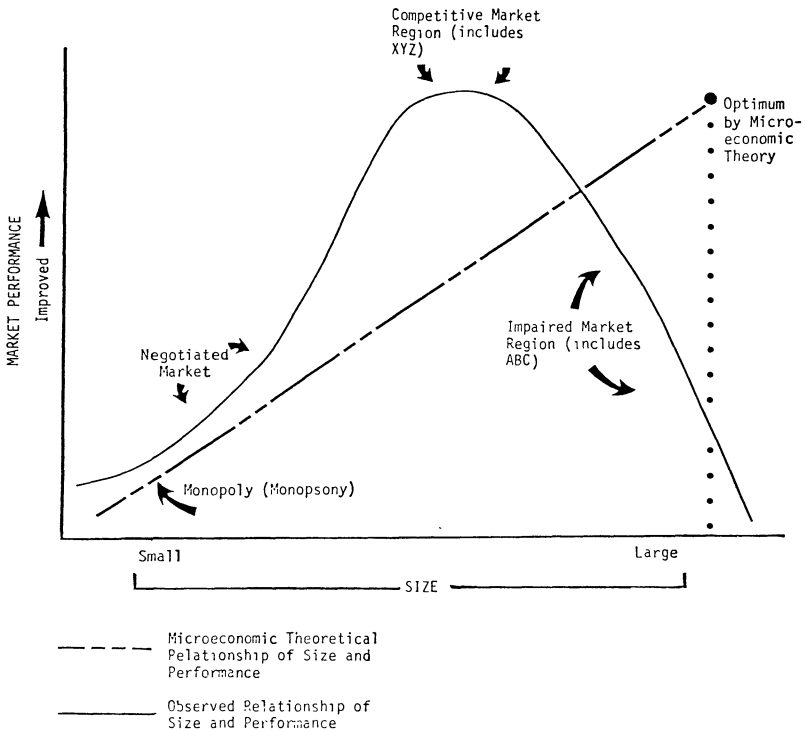


FIG. 4.—Microeconomic theoretical and observed relationships of market size and market performance.

curve are derived from the qualitative data (see Baker, in press). At the extreme low end, a monopoly (monopsony) situation exists. Here there is only a single seller (buyer) in the options market crowd. The price at which transactions will occur in this situation is largely determined by the monopolist (monopsonist). Although this has occurred at the Exchange, it is much more common at other Exchanges.¹² In a somewhat larger market, a phenomenon known as the “negotiated market” has been reported to occur. In this situation, prices are negotiated rather than determined by competitive bidding. The crowd is large enough to avoid a monopoly (monopsony) situation but small enough that actors can make greater profits by coordinating trading and sharing orders than by competing aggressively with one another.¹³ Such cooperation is a minor form of opportunism known as price fixing. Beyond the negotiated market is the range of market sizes that generate truly competitive markets (this is the area in which XYZ market operates). After this optimum range, market size and performance are related inversely (this is the area where ABC operates).

The specific relationship of size and performance represented by figure 4 is likely to apply to other Exchange-based markets in the securities and futures industry. The general nonlinear relationship of size and performance may apply as well to empirical markets that are not Exchange based, but further research on other empirical markets is required to specify the precise relationship of size and performance.

To economists, the finding that crowds on the floor of an Exchange grow so large that communication is impaired and price volatility increased is captured in the concept of “transaction costs.” For some time, several economists have argued that the comparatively high transaction costs of floor trading could be eliminated by replacing it with electronic trading (trading in which orders are displayed and matched by impersonal computer algorithms) (e.g., Mendelson and Peake 1979; Burns 1982). Electronic trading would indeed circumvent the communication problems and constraints on information flows associated with large and differentiated crowds like ABC. But electronic trading would be at best a mixed blessing, for electronic trading can never eliminate the facts that

¹² Monopoly (monopsony) situations are more likely to occur at Exchanges that utilize the “specialist system” of trading. In the specialist system, competing market makers do not exist; instead, a single person (the specialist) trades from his own account to make markets. In this role, the specialist acts as a dealer. As the only person to make markets, the specialist can be in a position to act as a monopolist (monopsonist). In addition, the specialist also handles the book of unexecuted public orders and thus acts as a broker. The dual roles of the specialist—dealer and broker—invariably create role conflict in that the duties of dealer and broker are inherently contradictory (see Baker, in press).

¹³ The production markets studied by Harrison C. White fit approximately into the “negotiated market” region (White, personal communication; White 1984).

human actors are subject to bounded rationality and that some actors will act opportunistically. Though orders could be matched by a computer algorithm, the buyers and sellers who place these orders are still subject to bounded rationality and still operate in an environment of uncertainty and complexity. Furthermore, while electronic trading would eliminate the abuses associated with floor trading (Burns 1982), it would simultaneously create new possibilities for opportunism, such as various forms of computer crime. Changing the contact technology of the market would affect the social structure of the market, but it would never escape the fact that markets are socially structured.

The results of this study have public policy implications made even more important by the recent rapid proliferation of new financial markets that are Exchange based. Both the Exchanges themselves and their federal regulators base policy decisions on the presumption that securities and futures markets are not socially structured. But as this analysis demonstrates, the options market is socially structured in ways that substantially affect its operations and outcomes. Exacerbated price volatility (ABC market) is inconsistent with the regulatory goal of “fair and orderly” markets. This makes it incumbent on the Exchanges and their regulators to investigate and ameliorate the detrimental effects caused by trading in large crowds. Limiting the size of crowds might be an effective (though exceedingly unpopular) way to accomplish this.

Part of the power and the appeal of economic models is that they provide normative guidance. For example, options valuation models (e.g., Black and Scholes 1972, 1973) are based on the concept of “fair value”—an estimate of what the price of an option *should* be in an efficient market. Empirical prices are compared with “fair value” to determine if an option is “overvalued” or “undervalued” in the market. The results of the present study also provide normative guidance, though not the kind that aids investors because the critical determinant of price volatility—the social structure of the market—is invisible to most participants.

Price volatility is used by investors as an important indicator of the risk of holding a security and of the intrinsic value of the assets represented by a security. Both exacerbated and dampened option price volatility present distorted information about the “true” volatility of prices—what volatility *should* be if markets were not socially structured. Such distortions are likely to result in misallocations of funds among markets. Exacerbated price volatility makes a security appear to be much riskier than it should be; conversely, dampened price volatility makes a security appear to be less risky than it should be. Conservative investors (risk averters) would tend to shun the first market and enter the second; speculators (risk assumers) would be attracted to the first market and tend to ignore the second. Although one may only speculate about the effects of such

migration patterns, the attraction of speculators to a market with already exacerbated price volatility might result in even more volatile prices; in the extreme, this might create a speculative bubble of some sort. The attraction of conservative investors to a market with lowered price volatility could result in a further decrease in price volatility, but it could instead, by increasing size, counterbalance lowered volatility and start to exacerbate price volatility.

Exacerbated and dampened price volatilities also affect investors who use derivative markets (options, futures) to reduce the risk of holding a position in an underlying market. For example, an investor with an exposed position in the stock market may offset some of the risk of adverse price movements by taking a position in the stock options market (or the stock index futures market). But exacerbated option price volatility introduces an additional element of risk to the investor. Dampened option price volatility, in contrast, enhances the use of options as a tool for reducing risk.

The social structure of the options market also affects the corporations whose stocks are listed for options trading. One of the presumed merits of listing a corporation's stock for options trading is that an active options market seems to reduce the volatility of underlying stock prices and reduced volatility reduces the corporation's cost of capital (Gastineau 1979, pp. 192–93). This may happen if option prices are made less volatile by the social structure of the options market. But exacerbated option price volatility may have a detrimental effect on underlying stock prices. If it did, the corporation's cost of capital would increase, and its ability to form new capital would be impaired.

Every corporation watches the volatility of the price of its securities in order to decide if and when to issue new securities. A firm may perceive exacerbated price volatility as an indicator that the market is too uncertain for issuing new securities. Conversely, a firm may perceive dampened price volatility as an indicator that the market will support the issuance of new securities. Both perceptions, however, are based on distorted information about the "true" volatility of prices and would result in ill-timed issues of new securities. The effects of basing decisions on socially structured prices are difficult to predict. Further research is needed to specify the effects of exacerbated and dampened price volatilities on investment decisions and ultimately on the ability of the financial markets to facilitate capital formation.

REFERENCES

- Abolafia, Mitchel. 1982. "Taming the Market: Self-Regulation in the Commodity Futures Industry." Ph D. dissertation, State University of New York at Stony Brook.
- . In press. "Structured Anarchy: Formal Organization in the Commodity Futures Industry." In Adler and Adler, eds., in press.

- Adler, Patricia A., and Peter Adler. 1980. "The Sociology of the Stock Market." Paper presented at the 75th annual meeting of the American Sociological Association, New York, August.
- Adler, Peter, and Patricia A. Adler, eds. In press. *The Social Dynamics of Financial Markets*. Greenwich, Conn.: JAI.
- Baker, Wayne E. 1976. "Inside the Chicago Board of Trade: A Participant's Observation." M.A. thesis, Northern Illinois University.
- . 1981. "Markets as Networks: A Multimethod Study of Trading Networks in a Securities Market." Ph.D. dissertation, Northwestern University.
- . 1982. "The Effects of Trading Networks on the Volatility of Option Prices." Paper presented at the 77th annual meeting of the American Sociological Association, San Francisco, Calif., September.
- . 1983. "Intermarket Structures: Modeling the Interrelationships of Markets and Traders." Paper presented at the 78th annual meeting of the American Sociological Association, Detroit, September.
- . In press. "Floor Trading and Crowd Dynamics." In Adler and Adler, eds., in press.
- Barber, Bernard. 1977. "Absolutization of the Market: Some Notes on How We Got from There to Here." Pp. 15–31 in *Markets and Morals*, edited by Gerald Dworkin, Gordon Bermant, and Peter G. Brown. Washington, D.C.: Hemisphere.
- Bernard, H. Russell, and Peter D. Killworth. 1977. "Informant Accuracy in Social Network Data II." *Human Communication Research* 4:3–18.
- Bernard, H. Russell, Peter D. Killworth, and L. Sailer. 1979/80. "Informant Accuracy in Social Network Data IV: A Comparison of Clique-Level Structure in Behavioral and Cognitive Network Data." *Social Networks* 2:191–218.
- Black, F., and M. Scholes. 1972. "The Valuation of Option Contracts and a Test of Market Efficiency." *Journal of Finance* 27:399–417.
- . 1973. "The Pricing of Options and Corporate Liabilities." *Journal of Political Economy* 81:637–54.
- Blau, Peter. 1970. "A Formal Theory of Differentiation in Organizations." *American Sociological Review* 35:201–18.
- Bookstaber, Richard M. 1981. *Option Pricing and Strategies in Investing*. Reading, Mass.: Addison-Wesley.
- Breiger, Ronald L. 1976. "Career Attributes and Network Structure: A Blockmodel Study of a Biomedical Research Specialty." *American Sociological Review* 41:117–35.
- Burk, James. 1982. "The American Stock Market: A Sociological Essay of Its Institutional Development, 1900–1975." Ph.D. dissertation, University of Chicago.
- Burns, Joseph M. 1979. *A Treatise on Markets: Spot, Futures, and Options*. Washington, D.C.: American Enterprise Institute.
- . 1982. "Electronic Trading in Futures Markets." *Financial Analysts Journal* (January–February), pp. 33–41.
- Burt, Ronald S. 1978. "Stratification and Prestige among Elite Experts in Methodological and Mathematical Sociology Circa 1975." *Social Networks* 2:105–58.
- Commodity Futures Trading Commission. 1982. "A Spotter's Guide to Commodity Fraud." Washington, D.C.: Division of Economics and Education, Commodity Futures Trading Commission.
- Debreu, Gerald, and Herbert Scarf. 1963. "A Limit Theorem on the Core of an Economy." *International Economic Review* 4:235–46.
- Doreian, Patrick. 1979/80. "On the Evolution of Group and Network Structure." *Social Networks* 2:235–52.
- Durkheim, Émile. 1893. *De la division du travail social*. Paris: Alcan.
- Faulkner, Robert. 1983. *Music on Demand: Composers and Careers in the Hollywood Film Industry*. New Brunswick, N.J.: Transaction.
- Festinger, Leon. 1950. "Informal Social Communication." *Psychological Review* 57:271–92.
- Festinger, Leon, Stanley Schacter, and Kurt Back. 1950. *Social Pressures in Informal Groups: A Study of Human Factors in Housing*. New York: Harper.
- Galaskiewicz, Joseph, and Stanley Wasserman. 1981. "A Dynamic Study of Change in a Regional Corporate Network." *American Sociological Review* 46:475–84.

American Journal of Sociology

- Gastineau, Gary. 1979. *The Stock Options Manual*. 2d ed. New York: McGraw-Hill.
- Glick, Ira. 1957. "A Social Psychological Study of Futures Trading." Ph.D. dissertation, University of Chicago.
- Hare, A. Paul. 1962. *Handbook of Small Group Research*. New York: Free Press.
- . 1976. *Handbook of Small Group Research*. 2d ed. New York: Free Press.
- Hawley, Amos H. 1971. *Urban Society*. New York: Ronald.
- Hayes, Samuel L., and Michael E. Tennenbaum. 1979. "The Impact of Listed Options on the Underlying Shares." *Financial Management* 8:72–76.
- Killworth, Peter D., and H. Russell Bernard. 1976. "Informant Accuracy in Social Network Data." *Human Organization* 35:269–96.
- . 1979. "Informant Accuracy in Social Network Data III, or A Comparison of Triadic Structure in Behavioral and Cognitive Data." *Social Networks* 2:19–46.
- Leblebici, Huseyin, and Gerald R. Salancik. 1982. "Stability in Interorganizational Exchanges: Rulemaking Processes of the Chicago Board of Trade." *Administrative Science Quarterly* 27:227–42.
- Logue, Dennis E. 1975. "Market-Making and the Assessment of Market Efficiency." *Journal of Finance* 30:115–23.
- Malinvaud, E. 1972. *Lectures on Microeconomic Theory*. Amsterdam: North-Holland.
- Martin, J. David, and Louis N. Gray. 1971. "Measurement of Relative Variation: Sociological Examples." *American Sociological Review* 36:496–502.
- Mayhew, Bruce H., and Roger L. Levinger. 1976. "Size and the Density of Interaction in Human Aggregates." *American Journal of Sociology* 82:86–110.
- Mayhew, Bruce H., Roger L. Levinger, J. Miller McPherson, and Thomas F. James. 1972. "System Size and Structural Differentiation in Formal Organizations: A Baseline Generator for Two Major Theoretical Propositions." *American Sociological Review* 37:629–33.
- McGrath, J. E., and I. Altman. 1966. *Small Group Research*. New York: Holt, Rinehart & Winston.
- Mendelson, Morris, and Junius W. Peake. 1979. "The ABCs of Trading on a National Market System." *Financial Analysts Journal* (September–October), pp. 31–42.
- Parsons, Talcott, and Neil J. Smelser. 1956. *Economy and Society*. New York: Free Press.
- Richards, William D., Jr. 1975. *A Manual for Network Analysis Using the NEGOPY Network Analysis Program*. Stanford, Calif.: Institute for Communication Research.
- Richards, William D., and Ronald E. Rice. 1981. "The NEGOPY Network Analysis Program." *Social Networks* 3:215–23.
- Rose, Arnold M. 1951. "Rumor in the Stock Market." *Public Opinion Quarterly* 15:461–86.
- . 1966. "A Social Psychological Approach to the Stock Market." *Kyklos* 19:267–88.
- Scherer, F. M. 1980. *Industrial Market Structure and Economic Performance*. Boston: Houghton Mifflin.
- Shepherd, William G. 1972. "The Elements of Market Structure." *Review of Economics and Statistics* 54:25–35.
- Simon, Herbert A. 1978. "Rationality as Process and as Product of Thought." *American Economic Review* 68:1–16.
- . 1982. *Models of Bounded Rationality: Behavioral Economics and Business Organization*, vol. 2. Cambridge, Mass.: MIT Press.
- Thibaut, J. W. 1950. "An Experimental Study of the Cohesiveness of Underprivileged Groups." *Human Relations* 3:251–78.
- Thomas, E. J., and C. F. Fink. 1963. "Effects of Group Size." *Psychological Bulletin* 60:371–85.
- Thompson, James D. 1967. *Organizations in Action*. New York: McGraw-Hill.
- U.S. Securities and Exchange Commission. 1978. "Report of the Special Study of the Options Markets to the Securities and Exchange Commission." Committee Print, 96th Cong., 1st sess.
- Weber, Max. 1947. *The Theory of Social and Economic Organization*. Translated by A. M. Henderson and Talcott Parsons. New York: Free Press.
- White, Harrison C. 1981a. "Production Markets as Induced Role Structures." Pp. 1–57 in

- Sociological Methodology 1981*, edited by Samuel L. Leinhardt. San Francisco: Jossey-Bass.
- . 1981b. "Where Do Markets Come From?" *American Journal of Sociology* 87:517–47.
- . 1984. "Varieties of Markets." In *Structural Sociology: Networks of Connectivity and Power*, edited by Barry Wellman and S. D. Berkowitz. Cambridge: Cambridge University Press.
- White, Harrison C., Scott A. Boorman, and Ronald L. Breiger. 1976. "Social Structure from Multiple Networks. I. Blockmodels of Roles and Positions." *American Journal of Sociology* 81:730–80.
- Williamson, Oliver E. 1975. *Markets and Hierarchies: Analysis and Antitrust Implications*. New York: Free Press.
- . 1979a. "Assessing Vertical Market Restrictions: Antitrust Ramifications of the Transaction Cost Approach." *University of Pennsylvania Law Review* 127:953–93.
- . 1979b. "Transaction Cost Economics. The Governance of Contractual Relations." *Journal of Law and Economics* 22:233–61.
- . 1981. "The Economics of Organization: The Transaction Cost Approach." *American Journal of Sociology* 87:548–77.