# Transmission of Volatility between Stock Markets

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***This article investigates why, in October 1987, almost all stock markets fell together despite widely differing economic circumstances. We construct a model in which "contagion" between markets occurs as a result of attempts by rational agents to infer information from price changes in other markets. This provides a channel through which a "mistake" in one market can be transmitted to other markets. We offer supporting evidence for contagion effects using two different sources of data.***

The stock market crash of October 1987 generated a large number of reports and commentaries. Most of these concentrated on the alleged failure of market mechanisms in particular countries, especially the United States, and largely ignored the question of why markets around the world fell simultaneously and with surprising uniformity (Figure 1).

The fact that stock markets in different countries are correlated is, of course, not surprising in itself. Any standard asset pricing model, such as the inter-

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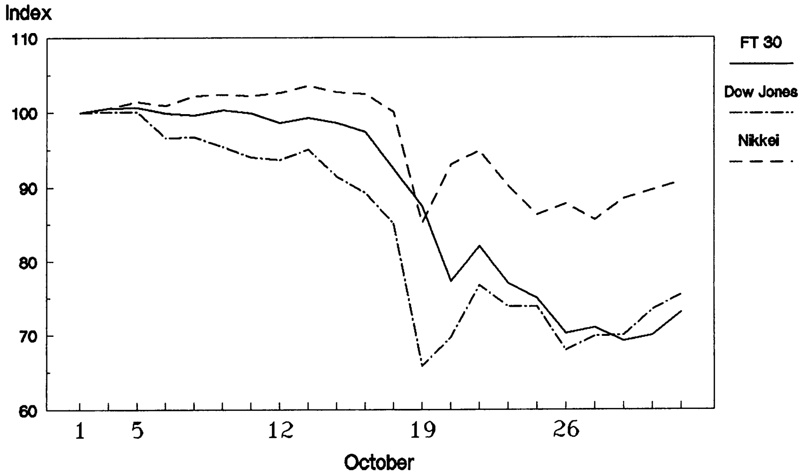


**Figure 1**
**Stock market indexes, October 1987 (October 1, 1987 = 100)**

national capital asset pricing model (ICAPM), would allow for such a correlation. But to interpret the data solely within a Walrasian equilibrium framework with fully informed agents seems inadequate for two reasons. First, it is difficult to come up with a credible story that links "fundamentals" to the crash; what could explain a fall of almost 23 percent, the largest one-day fall, on the NYSE? Moreover it is extremely hard to imagine that any such explanation would be consistent with the uniform decline in equity prices in different countries.[1] Second, the correlation coefficients between stock markets are remarkably unstable over time [Brady Report (1988)].

In this article we examine a rational expectations price equilibrium and model contagion between markets as the outcome of rational attempts to use imperfect information about the events relevant to equity values. Because investors (including market-makers) have access to different sets of information they can infer valuable information from price changes in other markets. Although published news should affect all markets at the same time (albeit in different ways because the significance of a piece of news may vary from country to country), not all information, nor the ability to process it, is public.

[1] Some commentators saw the crash as the end of a speculative bubble. Although there may be some truth to this story, there remains the puzzle of why the end of a bubble should have led to (1) similar falls in markets that had behaved in very different ways prior to the crash and (2) subsequent recoveries in markets, such as Tokyo, that had been most frequently cited as examples of speculative bubbles.

valuable information is contained in the prices that other traders are willing to pay. Hence, an individual trading in London may feel that information is revealed by the price changes in the New York and Tokyo stock exchanges. Observed price changes are used to infer other agents' information. In models of rational expectations equilibrium with asymmetric information market prices reveal all relevant information to agents, provided that the information structure is relatively simple [Bray (1985), Green (1977), Grossman (1976, 1978, 1981)]. When this is the case markets are strongly informationally efficient. Stock prices reflect fundamentals. But when the information structure is more complex the mapping from signals (the information observed by one agent that is relevant to others) to market prices will not be invertible, and so the equilibrium will be non-fully-revealing. In general, this will be true when the dimension of the signal space exceeds the dimension of the price space, or when the number of signals exceeds the number of markets [Jordan (1983)]. In a non-fully-revealing equilibrium price changes in one market will, therefore, in a real sense depend on price changes in other countries through structural contagion coefficients. Mistakes or idiosyncratic changes in one market may be transmitted to other markets, thus increasing volatility. It is this feature that appeals to us as an alternative to "news" as an explanation of the contemporaneous fall in all major stock markets in October 1987. For example, a failure in the market mechanism in one country that is not immediately recognized as such will be transmitted to other markets. Our principal aim is to explore the empirical implications of the idea that a non-fully-revealing equilibrium implies the possibility of contagion effects.

There is a fundamental identification problem in distinguishing between the Walrasian efficient markets and the non-fully-revealing rational expectations models. This is because, in the absence of any prior restriction on the way in which the covariance structure of returns may vary over time, any observed correlations between stock markets can be said to be consistent with an asset pricing model that satisfies the efficient markets hypothesis. Nevertheless, there are certain features of the data that throw light on the plausibility of the two models. Stock markets are not open 'round the clock. In the non-fully-revealing, but not the Walrasian equilibrium, model there is a jump in the price in all other markets when one market reopens, reflecting the information contained in the value of the opening price. This provides one clear-cut test of the model, and we pay particular attention to the modeling of price changes when there is time zone trading.

As was mentioned above it is well known that the links between stock markets vary over time, and we provide further supporting evidence below. The interesting question is whether the time-varying covariance structure can be modeled in a plausible manner. We explore the idea that the correlation between markets rises following an increase in volatility. Using monthly data the Brady Report (1988) found that annual covariances were not stable and did not exhibit any clear trend. This they interpreted as evidence of the insignificance of international transmission of price volatility during the 1987 crash. With high-frequency data, however, we show that covariances are related to volatility in a way that is consistent with both the contagion model and also the observed low-frequency correlations. An implication of this result is that an increase in volatility could be self-reinforcing and persist for longer than would otherwise be the case. We conjecture that this might be one reason for the uniform fall in stock markets during October 1987, despite their varying experience both before and after that date. As volatility declines, market links become weaker, and price changes are less closely tied together.

Sections 1 and 2 set out the theoretical framework of the article. Estimates of the contagion model based on hourly data for London, New York, and Tokyo over the period July 1987 to February 1988 are described in Section 3. These suggest that the contagion coefficients increased during the crash. Our conclusions are presented in Section 4.

## 1. An Example with Two Markets

For simplicity, especially when we come to model time zone trading, we consider the case of risk-neutral investors. There is, however, a cost to this assumption. With risk neutrality and arbitrage between stock markets, all information is fully revealed. To prevent this we assume that there is no trading in stocks across frontiers. There are three reasons for making this assumption. First, it makes possible a non-fully-revealing equilibrium with risk-neutral investors that permits a linear structure for price changes. Second, in practice prices are not determined by a Walrasian auctioneer, and uninformed (in this case foreign) investors know that information will be revealed to them by past transaction prices rather than notional prices transmitted by an auctioneer. Third, even though developments in information technology mean that market-makers and many large investors in different countries now receive news simultaneously, the implication of screen-based news for prices is not costless to calculate. There is a difference between "news" that arrives on screens and "news" in the sense of unanticipated revaluations of asset prices. It is costly to process the former to yield the latter. Some, perhaps many, investors may find it less costly to infer valuations, albeit imperfectly, from changes in market prices than to incur the direct costs of processing information. As a modeling strategy, therefore, we want to analyze a non-fully-revealing equilibrium. Although this is perfectly compatible with international trading in stocks, the greater complexity involved in modeling the behavior of risk-averse investors, especially with time zone trading, adds little to the implications of empirical work.

The model is best illustrated by considering the case of two countries, both with their own stock market. The general case is examined in Section 3. Assume first that both markets are open 'round the clock. The change in the stock market index over an hourly period, say, is a function of the news released between the beginning and the end of that hour. Information is of two types, systematic and idiosyncratic. The former, denoted by $u$, is information that affects market values in both countries. The latter, denoted by $v$, is relevant only to a specific country. Both $u$ and $v$ are assumed to comprise two components, corresponding to information that is observed in one country or the other. Consider, first, a fully revealing equilibrium. If information from both countries were fully revealed, then the process that would generate changes in stock prices is assumed to be

$$\Delta S_t^{(1)} = u_t^{(1)} + \alpha_{12} u_t^{(2)} + v_t^{(1)} \tag{1}$$

$$\Delta S_t^{(2)} = \alpha_{21} u_t^{(1)} + u_t^{(2)} + v_t^{(2)} \tag{2}$$

where $\Delta S_t^{(j)}$ denotes the percentage return in country $j$ between time $t - 1$ and time $t$ measured by the change in the logarithm of the stock market price index. The superscripts on the information variables denote the country in which that information is observed. The four information variables are assumed to be uncorrelated and to follow a white-noise process. The only economic restriction implied by this (and, in particular, the assumption that $u^{(1)}$ and $u^{(2)}$ are independent) is that news which affects both countries is always revealed (or interpreted) first in one country or the other, but never simultaneously. This assumption is made purely for convenience. The consequences of relaxing it are minor and are discussed in the Appendix.

If information is not fully observable in both markets, then investors and market-makers set prices according to

$$\Delta S_t^{(1)} = u_t^{(1)} + \alpha_{12} E_1(u_t^{(2)}) + v_t^{(1)} \tag{3}$$

$$\Delta S_t^{(2)} = \alpha_{21} E_2(u_t^{(1)}) + u_t^{(2)} + v_t^{(2)} \tag{4}$$

where $E_1$ and $E_2$ denote the expectations operator conditional upon information observed in markets 1 and 2, respectively. We assume that the only information available to market 1 about the value of $u^{(2)}$ is the contemporaneous price change in market 2. The unconditional expectation of $u^{(2)}$ in market 1 is zero, but a nonzero realization of $\Delta S_t^{(2)}$ provides information to market 1 about the information that has been observed in market 2. The message is contaminated by the fact that some information which leads to price changes in market 2 is idiosyncratic and irrelevant to market 1. Hence the equilibrium is not fully revealing. In addition market 1 players realize that their counterparts in market 2 are going through the same exercise in order to infer information from price changes in market 1. We assume that the distributions of the stochastic news processes and the parameters of the model are common knowledge. Hence agents can solve the signal extraction problem to find the minimum-variance estimator for the value of the relevant news term that has been observed in the other market. The solution to this problem is

$$E_1(u_t^{(2)}) = \lambda_2[\Delta S_t^{(2)} - \alpha_{21}E_2(u_t^{(1)})] \tag{5}$$

$$E_2(u_t^{(1)}) = \lambda_1[\Delta S_t^{(1)} - \alpha_{12}E_1(u_t^{(2)})] \tag{6}$$

where $\sigma_x^2$ denotes the variance of $x$ and

$$\lambda_i = \frac{\sigma_{u(i)}^2}{\sigma_{u(i)}^2 + \sigma_{v(i)}^2} \qquad i = 1, 2 \tag{7}$$

Substituting these expressions back into Equations (3) and (4) yields[2]

$$\Delta S_t^{(1)} = (1 - \alpha_{12}\alpha_{21}\lambda_1\lambda_2)(u_t^{(1)} + v_t^{(1)}) + \alpha_{12}\lambda_2\, \Delta S_t^{(2)} \tag{8}$$

$$\Delta S_t^{(2)} = (1 - \alpha_{12}\alpha_{21}\lambda_1\lambda_2)(u_t^{(2)} + v_t^{(2)}) + \alpha_{21}\lambda_1\, \Delta S_t^{(1)} \tag{9}$$

Because the $\alpha$ and $\lambda$ parameters cannot be separately identified we define

$$\beta_{ij} = \alpha_{ij}\lambda_j \qquad i, j = 1, 2 \tag{10}$$

Denote

$$\eta^{(i)} = u^{(i)} + v^{(i)} \qquad i = 1, 2 \tag{11}$$

[2] When $u^{(1)}$ and $u^{(2)}$ are correlated we obtain equations that are analogous to (8) and (9). These are derived in the Appendix. We have also made the simplifying assumption that agents in one market never learn subsequently about past realizations of the random variable $u$ in other markets. When agents learn in later periods about the currently unobservable news the mistakes in valuation are corrected. This adds noise to the price changes but induces no serial correlation. The correlation coefficient between markets is equal to its value in the fully revealing model. The implications for price jumps as discussed below are unchanged. Details of this "catch-up" model are available on request.

**Table 1**
**Volatility in the two-market case**

| | Variance of market 1 | Variance of market 2 | Covariance |
|---|---|---|---|
| Full information | $\sigma^2_{\eta(1)} + (\alpha_{12})^2\sigma^2_{u(2)}$ | $\sigma^2_{\eta(2)} + (\alpha_{21})^2\sigma^2_{u(1)}$ | $\alpha_{21}\sigma^2_{u(1)} + \alpha_{12}\sigma^2_{u(2)}$ |
| Contagion model | $\sigma^2_{\eta(2)} + \lambda_2(\alpha_{12})^2\sigma^2_{u(2)}$ | $\sigma^2_{\eta(2)} + \lambda_2(\alpha_{21})^2\sigma^2_{u(2)}$ | $\alpha_{21}\sigma^2_{u(1)} + \alpha_{12}\sigma^2_{u(2)}$ |
| No communication | $\sigma^2_{\eta(1)}$ | $\sigma^2_{\eta(2)}$ | 0 |

Solving Equations (8) and (9) simultaneously we obtain

$$\Delta S_t^{(1)} = \eta_t^{(1)} + \beta_{12}\eta_t^{(2)} \tag{12}$$

$$\Delta S_t^{(2)} = \eta_t^{(2)} + \beta_{21}\eta_t^{(1)} \tag{13}$$

With 'round the clock trading the variances and covariances of stock price changes are

$$\mathrm{var}(\Delta S^{(1)}) = \sigma^2_{\eta(1)} + (\beta_{12})^2\sigma^2_{\eta(2)} \tag{14}$$

$$\mathrm{var}(\Delta S^{(2)}) = \sigma^2_{\eta(2)} + (\beta_{21})^2\sigma^2_{\eta(1)} \tag{15}$$

$$\mathrm{cov}(\Delta S^{(1)}, \Delta S^{(2)}) = \beta_{21}\sigma^2_{\eta(1)} + \beta_{12}\sigma^2_{\eta(2)} \tag{16}$$

We have concentrated on the case where the underlying variances are constant. However, the analysis carries over to the case in which the variances vary over time, and in our empirical work we will examine changes in $\beta_{ij}$ that might occur as a result of changes in $\lambda_j$.

The covariance structure of stock price changes in this model may be compared with that in two polar cases; first, the fully revealing equilibrium described by Equations (1) and (2) in which all information is either available at the same time in both countries or may be inferred from prices, and, second, the other extreme in which there is no communication at all between the markets and the price change in market $j$ is simply $\eta^{(j)}$. Table 1 shows the values of the variances and covariance in all three cases [using Equations (7), (10), and (11)]. The variance of stock price changes in both markets is higher in the fully revealing equilibrium than in the imperfectly revealing equilibrium, which in turn exceeds the variance in the case of no communication. These results follow from the assumption of the rational use of available information. The covariance between the markets is identical in the fully revealing and the imperfectly revealing equilibria, and hence the correlation coefficient is higher in the latter case.

Consider the effect of an idiosyncratic shock in one market on prices in the other market. In both the fully revealing and no communications equilibria the impact of such a shock is zero. But in the non-fully-revealing equilibrium the elasticity of the change in the price in market $i$ with respect to an idiosyncratic shock in market $j$ is $\beta_{ij}$. It is because of this effect, and the resulting higher correlation coefficient between the markets, that we call the imperfectly revealing equilibrium the *contagion model.*

The contagion model described by Equations (14) to (16) is not fully identified because there are four parameters and only three pieces of information from the data. As we now show, however, the fact that markets operate in different time zones anad are closed for part of the day may help us to identify the contagion coefficients.

Each of the three markets examined in our empirical work is closed for a significant part of the day. The length of time for which markets operate has been increasing, but the indices are computed and published only for a certain number of hours each day. Only London and New York have overlapping trading hours. During the sample period used in our empirical work both the United States and United Kingdom changed from daylight saving (or summer) time to winter time on October 25.

When a market is closed there is no explicit index of prices. But we may define the *shadow* index as the price that would clear the market if trading were to take place conditional upon the information that is available when it is closed. Although the shadow index is unobservable, the concept plays an important role in our model.

**Case 1: overlapping trading hours.** In the two-market case there are, in general, four regimes in which trading may occur. Without loss of generality market 1 is defined to be that which opens first.

- Regime 1: Both markets are open and price changes are described by Equations (12) and (13).
- Regime 2: Market 1 is closed but market 2 remains open. Investors in market 2 can no longer use information from market 1 to form conditional expectations about the value of $u^{(1)}$. Because the unconditional expectation is zero, then from Equation (4) the price change in market 2 in regime 2 is given by

$$\Delta S_t^{(2)} = \eta_t^{(2)} \tag{17}$$

In market 1 the shadow index incorporates information directly observable in market 1 as well as the information that is inferred from the actual price change in market 2. Hence (using the superscript $s$ to denote the shadow index) we have[3]

$$\Delta S_t^{(1s)} = \eta_t^{(1)} + \beta_{12}\Delta S_t^{(2)} \tag{18}$$

[3] If $u^{(1)}$ and $u^{(2)}$ are correlated, then Equations (17) and (18) are no longer valid. The coefficient in (18) is no longer equal to the corresponding coefficient in (8) when both markets are open. This implies that the estimates of the contagion coefficients from overlapping trading hours and open-to-close regressions need not coincide.

- Regime 3: Both markets are closed and the shadow price changes are given by

$$\Delta S_t^{(is)} = \eta_t^{(i)} \qquad i = 1, 2 \tag{19}$$

- Regime 4: Market 2 is closed and market 1 is open. This situation is obviously the mirror image of regime 2 and price changes are described by Equations (17) and (18) with superscripts 1 and 2 interchanged.

It is necessary to examine also the *jumps* in price that take place when switching from one regime to another. Such jumps occur whenever a market reopens and are a unique feature of the imperfectly revealing equilibrium model. There are two cases to examine. First, when market 1 reopens the shadow index in market 2 jumps to reflect the information that is contained in the opening price in market 1. Denote by $t_{oi}$ and $t_{ci}$ the times at which market $i$ opens and closes, and by $S_{oi}^{(j)}$ and $S_{ci}^{(j)}$ the logarithm of the stock price in market $j$ at the time when market $i$ opens and closes, respectively.[4] The change in price between the close of trading on one day and the opening of trading on the next day, the "close-to-open" (CO) price change, is defined (for market $j$) by

$$\mathrm{CO}^{(j)} \equiv S_{oj}^{(j)} - S_{cj}^{(j)} \tag{20}$$

Denote by $J_i^{(j)}$ the jump in the (actual or shadow) price in market $j$ when market $i$ reopens. When market 1 reopens market 2 is closed and so there is a jump in the *shadow* price in market 2. This is equal to the inferred value of the relevant information contained in the opening price in market 1 allowing for the fact that market 1 itself is reacting to information revealed by the previous day's change in market 2 after market 1 had closed.

$$J_1^{(2)} = \beta_{21}[\mathrm{CO}^{(1)} - \beta_{12}(S_{c2}^{(2)} - S_{c1}^{(2)})] \tag{21}$$

When trading commences in market 1, the opening price will reflect the market's reaction to the price changes in market 2 that occurred when market 1 was shut. The close-to-open price change in market 1 is the sum of the changes in the shadow price from regime 2 (while market 2 remains open) and from regime 3 (while both markets are closed). Hence

$$\mathrm{CO}^{(1)} = \sum_{t=t_{c1}}^{t_{o1}} \eta_t^{(1)} + \beta_{12}(S_{c2}^{(2)} - S_{c1}^{(2)}) \tag{22}$$

[4] To simplify notation we omit the day to which these values refer. This should be obvious from the context.

Combining Equations (21) and (22) yields the price jump as

$$J_1^{(2)} = \beta_{21} \sum_{t=t_{c1}}^{t_{o1}} \eta_t^{(1)} \tag{23}$$

The opening price in market 1 reveals to market 2 the accumulated value of the total news terms $\eta^{(1)}$ since the market closed on the previous day. This revelation property of the opening price is a general result. Given their assumed knowledge of the structure of the problem, agents in all other markets can infer the accumulated value of the total news term in any market that has just reopened.

The second case is when market 2 reopens, and market 1 is open so that there is a jump in the *actual* price in market 1 given by

$$J_2^{(1)} = \beta_{12}[\mathrm{CO}^{(2)} - \beta_{21}(S_{o2}^{(1)} - S_{c1}^{(1)})] + (\beta_{12})^2\beta_{21}(S_{c2}^{(2)} - S_{c1}^{(2)}) \tag{24}$$

The jump is equal to the inferred value of the information in the opening price in market 2 taking into account the reaction of market 2 to (1) the price changes earlier in the day in market 1 and (2) the opening price in market 1, which in turn reflects price changes in market 2 on the previous day after market 1 had closed.

The close-to-open price change in market 2 is the sum of the changes in the shadow price in regime 3 when both markets are closed [Equation (19)], the jump in the shadow price when market 1 reopens [Equation (21)], and the changes in the shadow price in regime 4 while market 1 is trading [Equation (18)]. Summing over this set of changes yields the close-to-open price change in market 2 as

$$\mathrm{CO}^{(2)} = \sum_{t=t_{c2}}^{t_{o2}} \eta_t^{(2)} + \beta_{21}(S_{o2}^{(1)} - S_{c1}^{(1)}) - \beta_{12}\beta_{21}(S_{c2}^{(2)} - S_{c1}^{(2)}) \tag{25}$$

Combining Equations (24) and (25), the jump in the price in market 1 when market 2 reopens is

$$J_2^{(1)} = \beta_{12} \sum_{t=t_{c2}}^{t_{o2}} \eta_t^{(2)} \tag{26}$$

The complete description of price changes with time zone trading consists of the equations for each of the four regimes [Equations (12), (13), (17), (18), and (19)] together with the equations for the jumps in price at the switch points that link regimes [Equations (23) and (26)]. The change in price over any finite period is the sum of the changes in either the actual or shadow prices over that period and is obtained by summing over the equations for the relevant regimes and switch points. Equations (22), (23), (25), and (26) can be regarded as a simultaneous system for the close-to-open price changes and the price jumps in the two markets.

In our empirical work we will use Equation (26) to examine the effect on London prices of the opening price in New York. In principle OLS estimation of Equation (22) yields a consistent estimator for the contagion coefficient $\beta_{12}$ because there is no problem of simultaneity. This is because market 2 is closed when market 1 reopens, so that there is no feedback from market 1 to market 2.[5]

**Case 2: nonoverlapping trading hours.** When trading hours do not overlap (London and Tokyo, for example) the outcome is symmetric. The equations governing price changes within regimes and at the jump points are as described above. In both markets the jump in the shadow price equals the informational content of the opening price of the other market, allowing in turn for that market's reaction to the earlier price change in its own market. Because the two markets do not overlap means that there is a recursive structure to the price jumps. For this reason it is convenient to examine changes in prices over the 24-hour period from the close of trading on one day to the close of trading on the next. Denote the "close-to-close" (CC) price change on day $d$ in market $j$ by $CC_d^{(j)}$, and the cumulative value of the total news term $\eta^{(j)}$ during the close-to-close period that ends on day $d$ by $N_d^{(j)}$. Let market 1 be the market that both opens and closes before market 2 opens. Summing over the price changes in regimes 3, 2, and 4, Equations (19), (18), and (17), respectively, and at the jump point [Equation (26)], yields the close-to-close change in market 1 as

$$CC_d^{(1)} = N_d^{(1)} + \beta_{12}\left[(S_{c2}^{(2)} - S_{o2}^{(2)}) + \sum_{t=t_{c2}}^{t_{o2}} \eta_t^{(2)}\right] \tag{27}$$

Substituting from Equation (17)

$$CC_d^{(1)} = N_d^{(1)} + \beta_{12} N_{d-1}^{(2)} \tag{28}$$

Similarly

$$CC_d^{(2)} = N_d^{(2)} + \beta_{21} N_d^{(1)} \tag{29}$$

Equations (28) and (29) are natural generalizations of Equations (12) and (13). The lag in Equation (28) but not in Equation (29) reflects the fact that market 1 opens and closes before market 2 trades. These two equations may be solved to yield

$$CC_d^{(1)} = \beta_{12} CC_{d-1}^{(2)} + (1 - \beta_{12}\beta_{21}L) N_d^{(1)} \tag{30}$$

$$CC_d^{(2)} = \beta_{21} CC_d^{(1)} + (1 - \beta_{12}\beta_{21}L) N_d^{(2)} \tag{31}$$

[5] When $u^{(1)}$ and $u^{(2)}$ are correlated IV estimation is required.

In both cases the close-to-close price change is linearly related to the previous close-to-close price change in the other market and a first-order moving average error process. These equations represent the reaction of market 1 to market 2, taking into account the fact that market 2 reacted to the close-to-close change in market 1 on the previous day ($CC^{(1)}_{d-1}$), which, in turn, had reacted to $CC^{(2)}_{d-2}$, and so on. This chain of reactions may be represented as a moving average process.

## 2. The Many-Markets Model

The model described above for the case of two markets may be generalized to any number of markets, although, as we have seen, estimation of the model with time zone trading introduces a number of complications. When markets overlap fully the equation describing price changes for the general case of $J$ markets is

$$\mathbf{\Delta S} = \boldsymbol{\eta} + \mathbf{Ae} \tag{32}$$

where

$\mathbf{\Delta S}$ = a $J \times 1$ vector of price changes
$\boldsymbol{\eta}$ = a $J \times 1$ vector of news terms
$\mathbf{A}$ = a $J \times J$ matrix of the $\alpha_{ij}$ coefficients ($\alpha_{jj} = 0, \forall j$)
$\mathbf{e}$ = a $J \times 1$ vector of expectations of $u$ held by agents in other markets

The solution to the signal extraction problem is

$$\mathbf{e} = \boldsymbol{\Lambda}(\mathbf{\Delta S} - \mathbf{Ae}) \tag{33}$$

where $\boldsymbol{\Lambda}$ is a $J \times J$ diagonal matrix with $\lambda_j$ as the $j$th element of the leading diagonal.

Combining Equations (32) and (33) yields

$$\mathbf{\Delta S} = (\mathbf{I} + \mathbf{B})\boldsymbol{\eta} \tag{34}$$

where $\mathbf{B} = \mathbf{A}\boldsymbol{\Lambda}$, and the $ij$th element, $\beta_{ij}$, is the response of market $i$ to changes in the price in market $j$.

$\mathbf{B}$ is the matrix of contagion coefficients. As we saw in the case of two markets, the contagion model has the property that an idiosyncratic shock (such as a market breakdown) in one market may have a multiplier effect on markets elsewhere. The matrix formulation provides tests of two interesting, albeit rather extreme, hypotheses. The first is that there are multiple equilibria so that the rate of change of prices is indeterminate. This occurs if the matrix $(\mathbf{I} + \mathbf{B})$ is singular so that there is no unique solution for the rate of change of market prices. In conditions of a crash, for example, the $\beta$ coefficients might rise to a level at which the matrix became singular. Second, if the matrix is decomposable, then there is a hierarchy of influence of markets on each other, which can be thought of as a *leader–follower* relationship.

The existence of time zone trading in the case of $J$ markets means that there are $2^J$ possible regimes, consisting of all possible combinations of markets being either open or closed. The model describing price changes within regimes is a switching regressions model with exogenous switching. The form of the equations governing price changes in any given regime is similar to Equation (34) with **B** replaced by the submatrix formed by deleting the rows and columns corresponding to the markets that are closed. The number and sequence of regimes are exogenous to the model and are determined by time zone differences and local hours of trading.[6] In addition there are up to $J$ jump points when markets reopen, and hence $J(J-1)$ jumps in actual or shadow prices. When any market reopens the accumulated value of the total news observed in that market is revealed to all other markets. When market $j$ reopens the jump in market $i$ is equal to

$$J_j^{(i)} = \beta_{ij} \sum_{t=t_{cj}}^{t_{oj}} \eta_t^{(j)} \qquad \forall\ i \neq j \tag{35}$$

One possible regression model is to take the close-to-open price change as the dependent variable with the changes during the trading day in the other markets prior to the opening of the dependent market as the independent variables. This procedure yields consistent estimates of the contagion coefficients. But more efficient estimates could be obtained by using the information contained in the opening prices of the independent markets that open while the dependent market is closed, as in the two-market analysis of the previous section. The implications for estimation in this case depend upon the degree of overlap of trading in the various markets.

## 3. Empirical Results

In this section we provide some empirical tests of the contagion model using high-frequency data from the stock markets in London, New York, and Tokyo for an eight-month period around the crash, July 1987 to February 1988. Together these three markets account for 80 percent of total world market capitalization.

[6] Local exchanges may choose their hours of trading in the light of experience of the price movements determined endogenously within the model and, if this is the case, then the regimes become endogenous to the model. The issue of the optimal length of the trading day is beyond the scope of this article.

### 3.1 Tests for price jumps

One of the features that distinguishes the contagion model from any fully revealing equilibrium model are the price jumps that occur in all markets whenever one market reopens. For example, when New York opens there is a jump in the London price reflecting the information contained in the New York opening price [Equation (35)]. In fact, for the three main financial centers, the effect of the New York open on London is the only example of an observable jump in the price of a market that is open. All other jumps are of shadow prices in markets that are closed. In practice such jumps may be attenuated for a variety of reasons. An S&P 500 futures contract is traded (albeit in a thin market) in Amsterdam prior to the opening of New York; some U.S. stocks are traded in London; and information about the state of the order books of specialists on the NYSE may be available to some market-makers in London. As a result the jumps in the London price when New York opens may not be as clear-cut in practice as they appear in the theoretical model.

The empirical test of such jumps is that, ceteris paribus, the volatility of prices in London should rise when New York opens. Using data on the FTSE-100 Index in London we computed the volatility of half-hourly returns at 15-minute intervals throughout the trading day. Since there are considerable changes in the average level of volatility over the sample period, intraday volatility was calculated for three different subperiods as shown in Figures 2 to 4.[7] Figure 2 shows the intraday volatility during the precrash period (July 1 to October 13—75 trading days).[8] There are three times at which volatility is significantly higher (at the 10 percent level) than during the rest of the day: (1) 9:15–9:45 A.M., (2) 11:15–11:45 A.M., and (3) 2:45–3:15 P.M. The first of these periods is just after the opening of trading during which the market is incorporating overnight news. The second is the half-hour around 11:30 A.M., which is the time at which all official economic statistics for the United Kingdom are announced. The third is just after the New York opening (which is at 2:30 P.M. London time). Note that this period is not one during which official U.S. economic statistics are released. This occurs at 1:30 P.M. London time, and it is striking that there is a significant decline in volatility in London around this time suggesting that London reacts more to New York's assess-

[7] The three subperiods were selected on the basis of differences in the average level of volatility. The results are not sensitive to the precise dates that were used and, in particular, to the choice of October 13 rather than October 16 for the end of the precrash subperiod.

[8] We have excluded the observation for 11:30 A.M.–12 noon on August 20, as it represents by far the largest single change in the subperiod (following an unexpected announcement of changes in interest rates) and distorts the graph. Including this observation increases volatility by 50 percent for that 30-minute period.


**Figure 2**
**Standard deviation of 30-minute returns using the FTSE-100 index, computed for 15-minute intervals, July 1–October 13, 1987**

ment of the statistics than to the news itself. Figure 2 appears to support the contagion model.

Figure 3 shows volatility in the subperiod from December 1 to the end of February (61 trading days) following the crash and its immediate aftermath.[9] There appear to be two peaks in volatility, the first at the start of trading and the second for the first hour after the opening in New York (although this is not statistically significant). Again there is some support for the idea that London reacts to the opening price in New York (i.e., 2:00–2:30 P.M.). Figure 4 relates to the subperiod including the crash and its aftermath (34 trading days). Here the local peak in volatility comes just before the official opening in New York. Anecdotal evidence suggests that there was much greater communication between traders in London and New York regarding the size of the latters' order books immediately after the crash. This would have the effect of bringing forward in time the effect of New York on London, as observed in Figure 4. These results are broadly supportive of the notion that the time around the New York opening is associated with unusually high volatility in London, although the response is more diffused than would be predicted by the simple theoretical model examined above.

### 3.2 Contemporaneous correlation between markets

To identify the contagion coefficients we estimate the model on hourly data for stock price changes in New York, Tokyo, and London for the

[9] In this subperiod we have excluded the observations for 1:30–2:00 P.M. on December 10 and January 15, which followed the announcement of U.S. trade figures and are clear outliers.

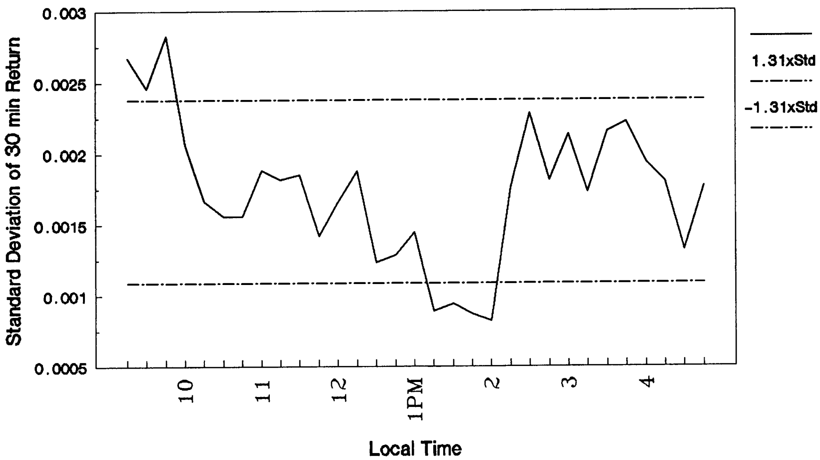


**Figure 3**
**Standard deviation of 30-minute returns using the FTSE-100 index, computed for 15-minute intervals, December 1, 1987–February 26, 1988**

period September to November 1987. For New York we use the Dow Jones Index, for London the Financial Times 30 Share Index, and for Tokyo the Nikkei-Dow Index.

One hypothesis to which we will pay particular attention is that the contagion coefficients increased during and immediately after the crash in response to the rise in volatility but then declined as volatility decreased. Nothing in the model implies that the contagion coefficients are necessarily constant. The variances of the information variables may change over time. Suppose that investors do not know the true variances of the information variables. With Bayesian updating of beliefs about variances a common shock to all markets, such as the crash, would result in an increase in the perceived variances of the common news terms. In turn this would lead to a rise in the contagion coefficients. Note that "common news" here refers to either fundamentals in the conventional sense or other sources of changes in equity values. If periods of high volatility exhibit little increase in economic "news" (e.g., episodes like the crash), then in such periods there is likely to have been a change in the underlying demand or "taste" for equity. As in the Keynesian beauty contest parable, changes in the average investor's taste for equity are important in determining the demands of individual investors, who, therefore, in times of increased volatility will rationally place greater weight on price changes elsewhere. In our sample period, therefore, we might expect that the contagion coefficients would be an increasing function of volatility.

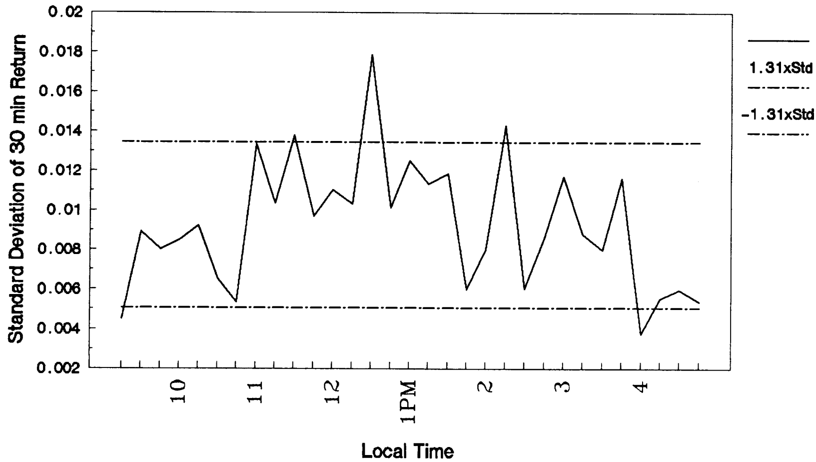


**Figure 4**
**Standard deviation of 30-minute returns using the FTSE-100 index, computed for 15-minute intervals, October 14–November 30, 1987**

Of the three markets that we consider only London and New York have overlapping trading hours. Denote London as market 1 and New York as market 2. The model that describes changes in stock prices when both markets are open is [from Equations (8) and (9)]

$$\Delta S_t^{(1)} = \beta_{12}\,\Delta S_t^{(2)} + (1 - \beta_{12}\beta_{21})\eta_t^{(1)} \qquad (36a)$$

$$\Delta S_t^{(2)} = \beta_{21}\,\Delta S_t^{(1)} + (1 - \beta_{12}\beta_{21})\eta_t^{(2)} \qquad (36b)$$

As we showed in Section 1, the contagion coefficients $\beta_{12}$ and $\beta_{21}$ are not identified from estimation of the model for overlapping trading hours because of the simultaneity involved. The imposition of identifying restrictions that would enable instruments to be constructed is discussed below.

When both markets are open it is difficult to distinguish the contagion model from a fully revealing equilibrium model such as the international market model (IMM). To see this suppose that price changes satisfy the IMM so that

$$\Delta S_t^{(i)} = \alpha_i + \beta_i\,\Delta S_t^{W} + \epsilon_t^{(i)} \qquad i = 1, 2 \qquad (37)$$

where

$\Delta S_t^W$ = the percentage change in the world index
$\beta_i$ = the normalized covariance with the world index
$\epsilon_t^{(i)}$ = the idiosyncratic component of the return

In the two-market case

$$\Delta S_t^W = w_1 \, \Delta S_t^{(1)} + w_2 \, \Delta S_t^{(2)} \tag{38}$$

where $w_i$ is the share of market $i$ in the world portfolio ($w_1 + w_2 = 1$). It is also true by construction that

$$w_1\beta_1 + w_2\beta_2 = 1 \tag{39}$$

From these equations it follows that

$$\Delta S_t^{(1)} = \frac{\beta_1}{\beta_2} \Delta S_t^{(2)} + \frac{\alpha_1 + \epsilon_t^{(1)}}{1 - \beta_1 w_1} \tag{40a}$$

$$\Delta S_t^{(2)} = \frac{\beta_2}{\beta_1} \Delta S_t^{(1)} + \frac{\alpha_2 + \epsilon_t^{(2)}}{1 - \beta_2 w_2} \tag{40b}$$

The difference between Equations (36) and (40) is that the IMM implies a nonlinear restriction on the regression coefficients. (In the two-market case the restriction is that the product of the coefficients is unity.) This restriction is rejected in our data. In the remaining empirical tests we focus on the change in the coefficients over time and in particular on their relationship with volatility. Whether these changes are more plausibly explained within a contagion model or in the IMM framework is a judgment that we leave to the reader.

First, however, we examine the correlation between the markets when both are open. Table 2 reports the correlation coefficient between London and New York for hourly price changes during overlapping trading hours (13:30 to 16:00 GMT), both before and after the crash. The correlation coefficient is positive, which is consistent with the idea of the contagion model. Using the published market index there is some evidence of an increase in the correlation between the two markets after the crash; the coefficient rises from 0.27 to 0.38. However, the published data for the United States may be misleading because, during the week of the crash, the Dow Jones Index often deviated from the "true" market-clearing price. For example, one hour after the opening bell on October 19 more than one-third of the stocks in the Dow Jones Index had failed to commence trading. In contrast, the futures price is more likely to reflect market-clearing levels (although the futures market itself shut down for a short period on October 20). It seems highly plausible that the observation that the futures price was often at a substantial discount to the cash price reflects the presence of "stale quotes" in the cash index.[10] In London

[10] Further discussion of this issue is contained in Miller et al. (1987).

**Table 2**
**Correlation between London and New York stock markets (hourly data for overlapping trading hours)**

| Sample period | Correlation coefficient | Number of observations |
|---|---|---|
| July 1–October 16, 1987 | .270 | 191 |
| October 19–November 30, 1987 | .379 | 86 |
| October 19–November 30, 1987[1] | .478 | 84 |
| December 1–February 28, 1988 | .194 | 175 |
| Crash week[1] | .649 | 10 |
| Crash week[2] | .750 | 10 |

[1] Uses data on the futures index for the United States during the crash week, as cash price data were unreliable.

[2] Uses data on the futures price index for both markets.

it has been argued by the International Stock Exchange that the official index "moved closely in step" with actual transactions prices, although there were occasions when the futures index traded at a discount.[11] For these reasons we recalculated the correlation coefficient using the percentage change in (1) the S&P futures price (quoted on the Chicago Mercantile Exchange) instead of the change in the Dow Jones Index and (2) the FTSE futures index (quoted on LIFFE) instead of the FT-30 Index for observations in the week of the crash. As can be seen from Table 2, this produces a significantly higher correlation coefficient of 0.48 during the period October 16 to the end of November, implying a substantial rise relative to the period before the crash and even higher values during the crash week itself. All the empirical results reported below are based on use of the futures index rather than the spot index for the United States during the crash week.[12] It is also striking that the correlation between the two markets had fallen to approximately its precrash level by the beginning of 1988.

There was a significant increase in actual volatility during the week of the crash (see Figure 5) in both London and New York. Measures of implied (or expected) volatility derived from observed option prices [using data from Franks and Schwartz (1988)] rose less than actual volatility, although the time pattern is similar (see Figure 6, which shows actual and implied standard deviations of hourly price changes in London during each week of the sample period). After the crash volatility fell, though it was not until February that it returned to its precrash level.

[11] *Quality of Markets Quarterly*, Winter 1987–1988, International Stock Exchange, London, p. 19.

[12] The futures data used during the crash week refer to the S&P Index, whereas we use the Dow Jones Index before and after the crash week. However, since the official Dow Jones Index during the crash week was unreliable, we believe that the change in the price of an S&P futures contract is likely to be a better proxy for the "true" change in the Dow Jones.

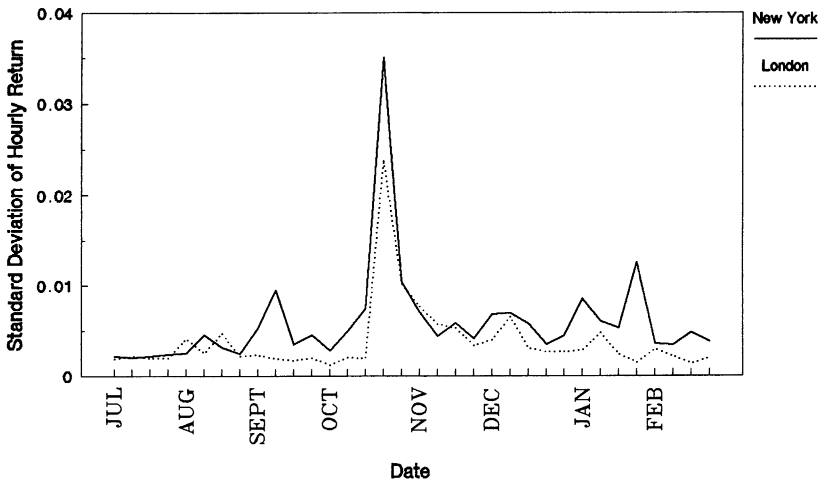


**Figure 5**
**Standard deviation of hourly returns computed over the previous week using the Dow Jones and FT-30 indexes, respectively**

Using the implied volatility measure we may test formally the hypothesis that the contagion coefficients are an increasing function of perceived volatility. When the product of the price change in the other market and the value of implied volatility is added to the regression model implied by Equation (36), there is striking evidence that the links between the two markets have indeed varied with changes in volatility. This may be seen in Table 3 (rows 1 and 2), where the columns headed VOL contain the regression coefficients of the variables measuring the interaction between implied volatility and the change in the other market. These coefficients are highly significant. They suggest that at the precrash mean of volatility (around 0.2), the response of both London and New York to a 1 percent change in the other was around 0.2–0.25 percentage points. During the five-week period starting from the crash week (during which volatility averaged about 0.5), London's response to changes in New York rose to around 0.5, and the coefficient on New York's response to London rose to an (implausibly high) point estimate of 1.3.

These results may not, of course, reflect contagion because regressions of hourly price changes in one market on changes in the other market are subject to simultaneity bias. But we explore the possibility of identifying the contagion coefficients through the use of instrumental variables (IV) estimation. If stock prices follow a martingale, as implied by the efficient markets hypothesis, then there are no observable variables that could be used as instruments. But there is now some evidence that stock returns are serially correlated [Fama

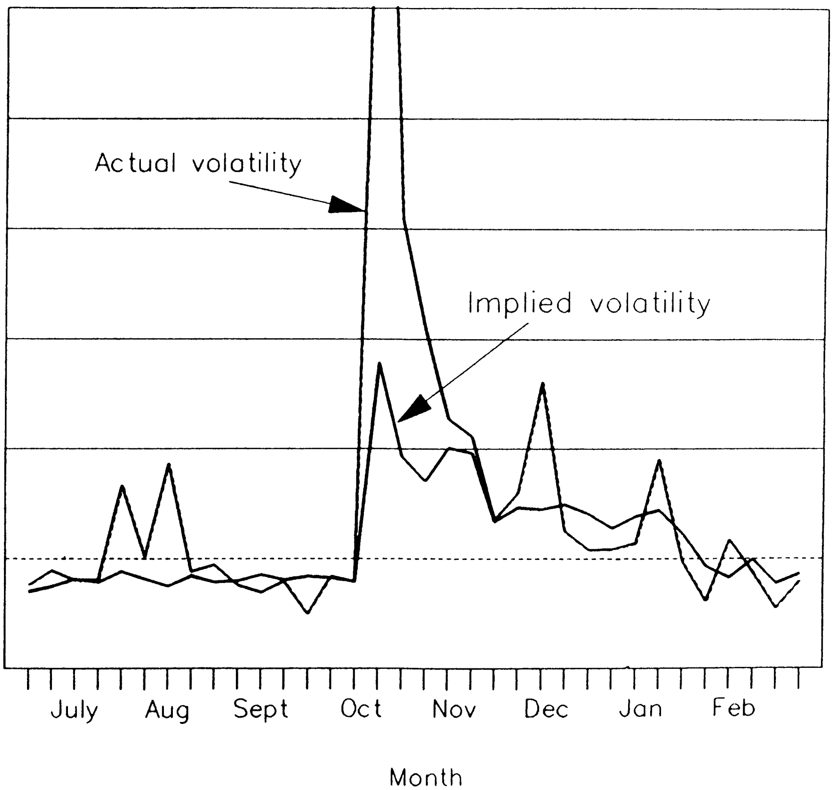


**Figure 6**
**Alternative measures of volatility, London**

and French (1986) and Poterba and Summers (1987)]. This may arise through either variations in expected returns or the activities of "noise" traders. With serially correlated returns, estimation of the following augmented version of Equations (40) would provide a way of identifying the contagion coefficients:

$$\Delta S_t^{(1)} = \beta_{12}\,\Delta S_t^{(2)} + \phi_1\,\Delta S_{t-1}^{(1)} + (1 - \beta_{12}\beta_{21})\eta_t^{(1)} \tag{41a}$$

$$\Delta S_t^{(2)} = \beta_{21}\,\Delta S_t^{(1)} + \phi_2\,\Delta S_{t-1}^{(2)} + (1 - \beta_{12}\beta_{21})\eta_t^{(2)} \tag{41b}$$

Hence lagged stock returns can be used as instruments in the estimation of Equations (41). When these equations were estimated using IV for the first and third subperiods the coefficients were poorly determined. This is probably because the serial correlation in hourly returns was greater during the crash week. Table 3, therefore, presents both OLS and IV estimates of Equations (41) for the subperiod that included the crash. The OLS estimates of the coefficients on lagged price changes

**Table 3**
**Estimates of the contagion coefficients between London and New York using overlapping data ($t$-values in parentheses)**

| Price change in | Sample period | Estimation method | $\beta_{12}$ | $\phi_1$ | $\beta_{21}$ | $\phi_2$ | VOL•$\beta^{r}$ | VOL•$\phi_2$ | Number of observations | $R^2$ | D.W. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| New York | July 1–Feb. 28 | OLS | — | — | −0.46 | 0.65 | 3.54 | −1.06 | 316 | 0.588 | 1.93 |
| | | | — | — | (−1.82) | (5.90) | (7.86) | (−5.00) | | | |
| London | July 1–Feb. 28 | OLS | −0.07 | 0.01 | — | — | 0.94 | — | 316 | 0.516 | 1.98 |
| | | | (−0.68) | (0.35) | — | — | (4.05) | | | | |
| New York | Oct. 19–Nov. 30 | OLS | — | — | 1.56 | 0.16 | — | — | 60 | 0.644 | 1.81 |
| | | | — | — | (9.14) | (2.05) | | | | | |
| London | Oct. 19–Nov. 30 | OLS | 0.36 | −0.09 | — | — | — | — | 60 | 0.628 | 1.80 |
| | | | (9.22) | (−1.25) | | | | | | | |
| New York | Oct. 19–Nov. 30 | IV | — | — | 2.16 | 0.09 | — | — | 60 | 0.568 | 1.74 |
| | | | — | — | (6.35) | (1.02) | | | | | |
| London | Oct. 19–Nov. 30 | IV | 0.41 | −0.08 | — | — | — | — | 60 | 0.630 | 1.74 |
| | | | (6.43) | (−0.98) | | | | | | | |

The most general equation that is estimated takes the form

$$\Delta S_t^{(2)} = \beta_{21}\, \Delta S_t^{(1)} + \phi_2\, \Delta S_{t-1}^{(2)} + \beta_2^{r}(\mathrm{VOL}_t)(\Delta S_t^{(1)}) + \eta_t^{(2)}$$

(analogous equation defined for market 1).

**Table 4**
**Estimates of the contagion coefficients between London and New York with time zone trading (*t*-values in parentheses)**

| | Sample period | 12 | 21 | Number of observations | $R^2$ | D.W. |
|---|---|---|---|---|---|---|
| United Kingdom [Equation (22)] | July 1–Oct. 13 | 0.21 (3.28) | — | 59 | 0.159 | 1.85 |
| | Oct. 14–Nov. 30 | 0.39 (6.06) | — | 29 | 0.576 | 2.80 |
| | Dec. 1–Feb. 28 | 0.36 (7.14) | — | 56 | 0.486 | 1.89 |
| United States [Equation (25)] | July 1–Oct. 13 | −0.09 (−0.23) | 0.18 (2.69) | 59 | 0.122 | 1.96 |
| | Oct. 14–Nov. 30 | 0.57 (4.23) | 1.11 (4.81) | 29 | 0.494 | 2.44 |
| | Dec. 1–Feb. 28 | 0.53 (3.85) | 0.44 (6.00) | 56 | 0.425 | 2.02 |

The equations estimated are

$$\mathrm{CO}^{(1)} = \sum_{t=t_{c1}}^{t_{o1}} \eta_t^{(1)} + \beta_{12}\,(S_{c2}^{(2)} - S_{c1}^{(2)})$$

and

$$\mathrm{CO}^{(2)} = \sum_{t=t_{c2}}^{t_{o2}} \eta_t^{(2)} + \beta_{21}\,(S_{o2}^{(1)} - S_{c1}^{(1)}) - \beta_{12}\beta_{21}\,(S_{c2}^{(2)} - S_{c1}^{(2)})$$

where 1 denotes the United Kingdom and 2 denotes the United States.

are significantly different from zero at the 5 percent level, as are the IV estimates. This suggests that there is a true interrelationship between the two markets and that the positive correlation coefficient is not explicable in terms of the same news arriving in both markets simultaneously. It is somewhat surprising, however, that the estimated contagion coefficients are slightly higher using IV than OLS estimation, implying that the innovations in news in the two markets were negatively correlated.

### 3.3 Time zone trading regression models

The model determining the close-to-open price changes incorporating interactions between London and New York is described by Equations (22) and (25). Table 4 shows estimates of the contagion coefficients based on this model. Rows 1, 2, and 3 show the estimates of Equation (22) for the United Kingdom for the three subperiods. This is the set of results obtained by regressing the close-to-open price change in London on the change in the New York price on the

**Table 5**
**Estimates of the contagion coefficients between Japan, United Kingdom, and United States with time zone trading (*t*-values in parentheses)**

| Regression | Sample | $\beta ij$ | $\beta ij \beta ji$ | Number of observations |
|---|---|---|---|---|
| London on Japan | July 1–Oct. 13 | 0.19 (3.31) | 0.01 (0.04) | 67 |
| | Oct. 14–Nov. 30 | 0.58 (7.33) | −0.46 (−2.88) | 31 |
| | Dec. 1–Feb. 28 | 0.06 (0.92) | −0.06 (0.46) | 58 |
| Japan on London | July 1–Oct. 13 | 0.17 (1.26) | 0.12 (1.00) | 66 |
| | Oct. 14–Nov. 30 | 0.26 (1.60) | −0.49 (−3.23) | 31 |
| | Dec. 1–Feb. 28 | 0.16 (1.22) | −0.34 (−2.73) | 58 |
| United States on Japan | July 1–Oct. 13 | 0.08 (1.38) | −0.19 (−1.58) | 71 |
| | Oct. 14–Nov. 30 | 0.16 (1.28) | −0.12 (−0.67) | 32 |
| | Dec. 1–Feb. 28 | 0.04 (0.60) | 0.09 (0.66) | 59 |
| Japan on United States | July 1–Oct. 13 | 0.20 (1.93) | 0.25 (2.13) | 70 |
| | Oct. 14–Nov. 30 | 0.49 (7.13) | −0.56 (−3.72) | 32 |
| | Dec. 1–Feb. 28 | 0.11 (1.12) | −0.20 (−1.56) | 59 |

The equations estimated take the form

$$CC_d^{(i)} = \beta_{ij} CC_{d-1}^{(j)} + (1 - \beta_{ij}\beta_{ji}L) N_d^{(i)}$$

previous day from the close of London to the close of New York. Rows 4, 5, and 6 show estimates of Equation (25) for the United States for each of the subperiods. This second set of estimates involves regressing the close-to-open price change in New York on the change in the London price from its previous close and on the change in the New York market on the previous day during the period when London was closed.

The message from the results shown in Table 4 is clear. They suggest a statistically significant association between the two markets, and, moreover, one that increases during mid-October and then declines after the end of November. The contagion coefficient measuring the effect of New York on London rose from an average of about 0.2 before the crash to about 0.4 after the crash. This is very much in line with the estimates based on hourly changes during contemporaneous trading, which show a rise from 0.20 to 0.38. As far as the effect of London on New York is concerned, the point estimates of the contagion coefficient in Table 5 imply a rise from approximately 0.2 before the crash to around unity in the immediate aftermath of the crash (a slightly smaller rise than was obtained with the contemporaneous data), and then a fall to about 0.4 in the period December–February.

The contagion coefficients between Japan and both London and New York are obtained by estimating Equations (30) and (31), which represent a regression of the close-to-close price change in market 1 on the previous close-to-close change in market 2 with a moving average error process. These estimates are shown in Table 5. The contagion coefficient measuring the effect of market $j$ on market $i$ is denoted by $\beta_{ij}$. The dependent variable is the change in the price in country $i$. The estimated moving average error process gives an estimate of the product of the contagion coefficients. All of the point estimates are consistent with the view that the contagion coefficients rose in the period during and immediately after the crash and then fell to previous levels in the third of our subperiods. The pattern of correlations between markets that is revealed by the data seems easier to reconcile with the contagion model than with a fully revealing or purely "fundamentals" model.

### 3.4 A direct test of contagion

The essence of the contagion model is that the trading of stocks in one market per se affects share prices in other markets, that is, share prices respond both to public information about economic fundamentals and to share-price changes elsewhere. In a related context French and Roll (1986) examined whether trading contributed to higher volatility by exploiting the fact that U.S. stock markets were closed on Wednesdays during the second half of 1968 in order to clear the settlement backlog. Our contagion model predicts that during these U.S. exchange holidays share prices in London would be less volatile than on other days. In contrast, a fully revealing equilibrium model would predict no change in volatility because there was no interruption in the flow of official and other news.

To discriminate between the two hypotheses we computed the variance of daily returns in London for various subperiods during 1968–1971. The results are shown in Table 6 and are striking. Although there was no difference between daily return volatility on Wednesdays and on other days of the week in the period 1969–1971, volatility in London on Wednesdays during the second half of 1968 was only two-thirds its average daily level on other days. This evidence is supportive of the contagion hypothesis.

**Table 6**
**Variances of daily returns in the United Kingdom**

| | Wednesday | Other days |
|---|---|---|
| July–December 1968 | 57.2 | 83.2 |
| January 1969–December 1971 | 124.5 | 123.9 |

### 3.5 Related work

The idea that there may be volatility spillovers across markets also has been examined by Hamao, Masulis, and Ng (1989). They used a GARCH-based model of volatility and found that higher lagged volatility in both own and other markets was associated with higher current volatility. This is consistent with a contagion model but could also be rationalized within a fully revealing equilibrium framework. In a study of the Tokyo Stock Exchange, Barclay, Litzenberger, and Warner (1989) concluded that volatility was caused by private information revealed through trading. Neumark, Tinsley, and Tosini (1988) examined the prices of stocks quoted both in New York and either London or Tokyo. They found that price differentials narrowed during the crash period. But this provides evidence only on the size of transactions costs that may limit arbitrage and throws no light on the signal extraction mechanism that underlies the contagion model.

## 4. Conclusions

A world in which investors infer information from price changes in other countries is also one in which a "mistake" in one market can be transmitted to other markets. If, for example, a failure in the market mechanism in the United States exacerbated the crash (and we remain agnostic about that), then this would have transmitted itself to other markets. Moreover, the empirical evidence suggests that an increase in volatility leads in turn to an increase in the size of the contagion effects. The rise in the correlation between markets just after the crash is evidence of this. Were this result to prove robust, it would have the important implication that volatility can, in part, be self-sustaining.

The starting point of this article was the uniformity of the fall in world stock markets during the October 1987 crash, despite important differences in economic prospects, market mechanisms, and their prior "degree of overvaluation." We believe that our story might provide a part of the explanation. The evidence on price jumps with time zone trading supports the contagion model and merits further research with data from other markets. The evidence that volatility in London was lower when the New York market was closed on some Wednesdays in 1968 provides support for the contagion model. The role of contagion should not be dismissed on the grounds that there has been no historical trend increase in correlations between markets. Nothing in our argument requires there to have been such an increase. Rather, it is the volatility-related increase in contagion effects that is the feature of the transmission mechanism.

The possibility of contagion means that one cannot assert that, because markets without formal portfolio insurance fell as much as the U.S. market, portfolio insurance could not have been responsible for the crash.[13] It is possible—though we take no position on this—that a U.S. price decline exacerbated by portfolio insurance could have spread to other markets.

## Appendix: Extensions of the Basic Model

### The contagion model when $u_1$, $u_2$ are correlated

Suppose that

$$\Delta S_t^{(1)} = u_t^{(1)} + \alpha_{12} u_t^{(2)} + v_t^{(2)} \tag{A1}$$

$$\Delta S_t^{(2)} = \alpha_{21} u_t^{(1)} + u_t^{(2)} + v_t^{(2)} \tag{A2}$$

as in the text, but instead of $u^{(1)}$ and $u^{(2)}$ being independent, we assume that

$$u_t^{(1)} = z_t + w_t^{(1)} \tag{A3}$$

$$u_t^{(2)} = z_t + w_t^{(2)} \tag{A4}$$

where $z_t$ represents the common component in $u_t^{(1)}$ and $u_t^{(2)}$. ($w_t^{(1)}$ and $w_t^{(2)}$ are independent.)

In this case, the solution to the signal extraction problems yields

$$E_1(u_t^{(2)}) = \chi_2[\Delta S_t^{(2)} - \alpha_{21} E_2(u_t^{(1)})] + \theta_2 u_t^{(1)} \tag{A5}$$

and

$$E_2(u_t^{(1)}) = \chi_1[\Delta S_t^{(1)} - \alpha_{12} E_1(u_t^{(2)})] + \theta_1 u_t^{(2)} \tag{A6}$$

where in contrast to the text, agents infer something about $u_t^{(i)}$ from the observed $u_t^{(j)}$. Note that

$$\chi_i = \lambda_i - \delta_i \theta_i > 0$$

[13] For a discussion of the plausibility of events in the U.S. market as the cause of the crash see Roll (1989) and Wadhwani (1989).

where

$$\lambda_i = \sigma^2_{u(i)}/(\sigma^2_{u(i)} + \sigma^2_{v(i)})$$

as before,

$$\delta_i = \sigma^2_z/(\sigma^2_z + \sigma^2_{w(i)} + \sigma^2_{v(i)})$$

and

$$\theta_i = \frac{(1 - \lambda_i)(1 - \delta_i)\sigma^2_z + \lambda_i\delta_i\sigma^2_{v(i)} - (1 - \lambda_i)\delta_i\sigma^2_{w(i)}}{(1 - \delta_i)\sigma^2_z + \sigma^2_{w(j)} + \delta^2_i\sigma^2_{w(i)} + \delta^2_i\sigma^2_{v(i)}}$$

Using (A5) and (A6), we can obtain

$$\Delta S^{(1)}_t = \frac{1}{M_1 + \alpha_{12}\alpha_{21}\chi_1}[\alpha_{12}\chi_2\,\Delta S^{(2)}_t + (M_1 + \alpha_{12}\theta_2)u^{(1)}_t + M_1 v^{(1)}_t] \quad \text{(A7)}$$

and

$$\Delta S^{(2)}_t = \frac{1}{M_2 + \alpha_{12}\alpha_{21}\chi_2}[\alpha_{21}\chi_1\,\Delta S^{(1)}_t + (M_2 + \alpha_{21}\theta_1)u^{(2)}_t + M_2 v^{(2)}_t] \quad \text{(A8)}$$

where

$$M_2 = 1 - \chi_1\chi_2\alpha_{21}\alpha_{12} + \chi_2\alpha_{21}\theta_1 > 0$$
$$M_1 = 1 - \chi_1\chi_2\alpha_{21}\alpha_{12} + \chi_1\alpha_{12}\theta_2 > 0$$

Therefore, (A7) and (A8) are just generalizations of Equations (8) and (9). The essence of the contagion model (i.e., a positive relationship between share-price changes, where the coefficient of interrelationship may vary as the ratios of different variances changes) is preserved.

The equations for the case of overlapping trading hours are also readily generalized. When both markets are closed, it is still possible to infer something about $u^{(j)}$ from $u^{(i)}$. So,

$$\Delta S^{(1s)} = (1 + \alpha_{12}\epsilon_1)u^{(1)} + v^{(1)} \quad \text{(A9)}$$
$$\Delta S^{(2s)} = (1 + \alpha_{21}\epsilon_2)u^{(2)} + v^{(2)} \quad \text{(A10)}$$

where

$$\epsilon_i = \sigma^2_z/(\sigma^2_z + \sigma^2_{w(i)})$$

If market 1 is closed but market 2 is open

$$\Delta S^{(1s)}_t = \frac{\alpha_{12}\chi_2}{K_1}[\Delta S^{(2)}_t + (1 + \alpha_{12}\theta_2)u^{(1)}_t + v^{(1)}_t]$$

where

$$K_1 = 1/(1 + \alpha_{21}\chi_2\sigma_z^2),$$

which is analogous to Equation (18).

Notice, however, that the coefficient of $\Delta S_t^{(2)}$ differs according to whether markets are open. This implies that our equations for "jumps" also will have to be correspondingly modified. Once again, though, the essential structure of the contagion model is unchanged.

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