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TRANSMISSION OF VOLATILITY BETWEEN STOCK MARKETS

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ABSTRACT

This paper investigates why, in October 1987, almost all stock markets fell together despite widely differing economic circumstances. The idea is that "contagion" between markets occurs as the 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. Hourly stock price data from New York, Tokyo and London during an eight month period around the crash offer support for the contagion model. In addition, the magnitude of the contagion coefficients are found to increase with volatility.

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Transmission of Volatility Between Stock Markets[1]

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1. Introduction

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 (see 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 International 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%, the largest one day fall since 1914, on the New York Stock Exchange? Moreover it is extremely hard to imagine that any such explanation would be consistent with the uniform decline in equity prices in different countries.[2] Secondly, the correlation coefficients

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

between stock markets are remarkably unstable over time (Brady Report,1988).

In this paper 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. 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 recognised 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 the efficient markets hypothesis and hence with some version of the ICAPM. 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 re-opens, 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 modelling of price changes when there is time zone trading. Other differences between the contagion model and the ICAPM are discussed when we turn to estimation.

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 modelled 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 neither stable nor exhibited 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 2 and 3 set out the theoretical framework of the paper. 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 4. These suggest that the contagion coefficients increased during the crash. Our conclusions are presented in section 5.

2. 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 modelling strategy, therefore, we want to analyse a non fully revealing equilibrium. Although this is perfectly compatible with international trading in stocks, the greater complexity involved in modelling the behaviour of risk averse investors, especially with time zone trading, adds little to the implications for 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. We assume that both u and v have two components, corresponding to information that is observed in one country or the other. If information from both countries were fully revealed then the process that would generate changes in stock prices is assumed to be

$$\Delta S^1_t = u^1_t + \alpha_{12}\, u^2_t + v^1_t \tag{1}$$

$$\Delta S^2_t = \alpha_{21}\, u^1_t + u^2_t + v^2_t \tag{2}$$

where ΔS^j_t denotes the change in the logarithm of the stock market price index in country j between time t-1 and time t. 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 below.

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

$$\Delta S^1_t = u^1_t + \alpha_{12}\, E_1(u^2_t) + v^1_t \tag{3}$$

$$\Delta S^2_t = \alpha_{21}\, E_2(u^1_t) + u^2_t + v^2_t \tag{4}$$

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 non-zero realisation of ΔS^2_t 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 realise 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

$$E_1(u^2_t) = \lambda_2 \left(\Delta S^2_t - \alpha_{21} E_2(u^1_t) \right) \tag{5}$$

$$E_2(u^1_t) = \lambda_1 \left(\Delta S^1_t - \alpha_{12} E_1(u^2_t) \right) \tag{6}$$

where σ^2_x denotes the variance of x and

$$\lambda_i = \frac{\sigma^2_{u^i}}{\sigma^2_{u^i} + \sigma^2_{v^i}} \qquad i = 1,2 \tag{7}$$

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

$$\Delta S^1_t = (1-\alpha_{12}\alpha_{21}\lambda_1\lambda_2)(u^1_t+v^1_t) + \alpha_{12}\lambda_2 \, \Delta S^2_t \tag{8}$$

$$\Delta S^2_t = (1-\alpha_{12}\alpha_{21}\lambda_1\lambda_2)(u^2_t+v^2_t) + \alpha_{21}\lambda_1 \, \Delta S^1_t \tag{9}$$

To simplify notation we define

[3] When u^1 and u^2 are correlated we obtain equations that are analogous to (8) and (9). We have also made the simplifying assumption that agents in one market never learn subsequently about past realisations of the random variable u in other markets. When there is a "catching-up" process of this type then the models developed below exhibit an ARIMA error process. We have checked, therefore, that the results are not subject to dynamic misspecification.

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

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

Solving (8) and (9) simultaneously we obtain

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

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

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

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

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

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

The covariance structure of stock price changes in this model may be compared with that in two polar cases; first, the fully revealing equilibrium in which all information is either available at the same time in both countries or may be inferred from prices, and, secondly, the other extreme in which there is no communication at all between the markets. 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 naturally from the assumption of rationality. In contrast, 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 β_{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)-(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 and 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 proportion 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. We measure time here in terms of GMT. Figure 2 shows the time periods for which each market trades.[4] Only London and New York have overlapping trading hours. During the sample period used in our empirical work both the US and UK changed from daylight saving (or summer) time to winter time on 25 October.

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. These are drawn schematically in Figure 3.

Regime 1: Both markets are open and price changes are described by equations (8) and (9).

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

[4] There is a break in the middle of the day in Tokyo that is not shown in the figure.

about the value of u^1. Because the unconditional expectation is zero then from equation (9) 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 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[5]

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

<u>Regime 3:</u> Both markets are closed and the shadow price changes are given by

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

<u>Regime 4:</u> 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 re-opens and are a unique feature of the imperfectly revealing equilibrium model. There are two cases to examine. First, when market 1 re-opens the shadow index in market 2 jumps to reflect the information that is contained in the opening price in market 1. Denote by $t^i_{o,d}$ and $t^i_{c,d}$ the times at which market i opens and closes, respectively on day d. 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" price change, is defined (for market j) by

$$\Delta S^j_{o,d+1} = S^j_{t^j_{o,d+1}} - S^j_{t^j_{c,d}} \tag{20}$$

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[5] 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). This implies that the estimates of the contagion coefficients from overlapping trading hours and open to close regressions need not coincide.

The jump in the shadow price in market 2 when market 1 re-opens on day d+1 is

$$\Delta S^{2S}_{t^{1}_{O,d+1}} = \beta_{21}\left(\Delta S^{1}_{O,d+1} - \beta_{12}\left\{ S^{2}_{t^{2}_{C,d}} - S^{2}_{t^{1}_{C,d}} \right\} \right) \qquad (21)$$

The jump is 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.

The second case is when market 2 re-opens, and there is a jump in the actual price in market 1 given by

$$\Delta S^{1}_{t^{2}_{O,d+1}} = \beta_{12}\left(\Delta S^{2}_{O,d+1} - \beta_{21}\left\{ S^{1}_{t^{2}_{O,d+1}} - S^{1}_{t^{1}_{C,d}} \right\} \right) + (\beta_{12})^{2}\beta_{21}\left(S^{2}_{t^{2}_{C,d}} - S^{2}_{t^{1}_{C,d}} \right) \qquad (22)$$

The complete description of price changes with time zone trading consists of the equations for each of the four regimes (equations (8), (9), (17), (18), and (19)) together with the equations for the jumps in price at the switch points that link regimes (equations (21) and (22)). 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.

In the case of overlapping trading hours it is convenient to work with close-to-open price changes, and this will be the basis for our empirical work. Consider, first, the close-to-open price change in market 1. 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

$$\Delta S^{1}_{O,d+1} = \sum_{t=t^{1}_{C,d}}^{t^{1}_{O,d+1}} \eta^{1}_{t} + \beta_{12} \sum_{t=t^{1}_{C,d}}^{t^{2}_{C,d}} \Delta S^{2}_{t} \qquad (23)$$

In principle OLS estimation of equation (23) yields a consistent estimator for the contagion coefficient β_{12} because there is no problem of simultaneity. This is because the jump in the shadow price in market 2 when market 1 re-opens has no feed-back effect on market 1 because market 2 is closed.[6]

This is the simpler case and the situation is less straightforward for the close-to-open price change in market 2 (as drawn in Figure 3). The reason is that the information from market 1 that is incorporated into the opening price in market 2 includes not only the price changes in market 1 after trading has started, but also the level of the opening price in market 1 itself 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), the jump in the shadow price when market 1 re-opens, and the changes in the shadow price in regime 4 (while market 1 is trading). Summing over this set of changes yields the close-to-open price change in market 2 as

$$\Delta S^{2}_{O,d+1} = \sum_{t=t^{2}_{C,d}}^{t^{2}_{O,d+1}} \eta^{2}_{t} + \beta_{21}\left(S^{1}_{t^{2}_{O,d+1}} - S^{1}_{t^{1}_{C,d}} \right) - \beta_{12}\beta_{21}\left(S^{2}_{t^{2}_{C,d}} - S^{2}_{t^{1}_{C,d}} \right) \tag{24}$$

Combining (21) and (23), and also (22) and (24), the jump in the price in market i when market j re-opens is

$$\Delta S^{i}_{t^{j}_{O,d+1}} = \beta_{ij} \sum_{t=t^{j}_{C,d}}^{t^{j}_{O,d+1}} \eta^{j}_{t} \tag{25}$$

The opening price reveals to the other market the accumulated value of the total news terms η since the market closed on the previous day. In our empirical work we shall use this equation to examine the impact on London prices of the opening price in New York. Equations (23)-(25) can be regarded as a simultaneous system for the close-to-open price changes in both markets and the jumps in the two markets when the other market re-opens.

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[6] When u^1 and u^2 are correlated IV estimation is required.

Case 2: Non-overlapping trading hours

When trading hours do not overlap (London and Tokyo, for example) the outcome is symmetric. The equations governing price changes within regimes are as described above. The only change is in the equation describing the jump in the shadow price when the other market re-opens. For the two markets these jumps are

$$\Delta S^{1S}_{t^2_{O,d}} = \beta_{12}\left(\Delta S^2_{O,d} - \beta_{21}\left\{ S^1_{t^1_{C,d}} - S^1_{t^1_{O,d}} \right\} - \Delta S^{2S}_{t^1_{O,d}} \right) \tag{26}$$

$$\Delta S^{2S}_{t^1_{O,d}} = \beta_{21}\left(\Delta S^1_{O,d} - \beta_{12}\left\{ S^2_{t^2_{C,d-1}} - S^2_{t^2_{O,d-1}} \right\} - \Delta S^{1S}_{t^2_{O,d-1}} \right) \tag{27}$$

In both markets the jump equals the informational content of the opening price of the other market allowing in turn for that market's reaction to the previous day's price change in the own market.

When trading hours are non-overlapping it is convenient to examine changes in prices from the close of trading on one day to the close of trading on the next. Define the "close-to-close" price change in market j as

$$\Delta S^j_{C,d+1} = S^j_{t^j_{C,d+1}} - S^j_{t^j_{C,d}} \tag{28}$$

Summing over the changes in the shadow prices in the relevant regimes and at the jump point, yields the close-to-close change in price in market 1 as

$$\Delta S^1_{C,d+1} = \sum_{t=t^1_{C,d}}^{t^1_{C,d+1}} \eta^1_t + \Delta S^{1S}_{t^2_{O,d}} + \beta_{12}(\Delta S^2_{C,d} - \Delta S^2_{O,d}) \tag{29}$$

Using the recursive nature of the jumps in shadow prices from (26) and (27), the close-to-close price change can be expressed as

$$\Delta S^{1}_{C,d+1} = \beta_{12}\Delta S^{2}_{C,d} + (1-\beta_{12}\beta_{21}L)\left(\sum_{t^{1}_{C,d}}^{t^{1}_{C,d+1}} \eta^{1}_{t} \right) \tag{30}$$

where L denotes the lag operator.

Similarly

$$\Delta S^{2}_{C,d+1} = \beta_{21}\Delta S^{1}_{C,d+1} + (1-\beta_{12}\beta_{21}L)\left(\sum_{t^{1}_{C,d}}^{t^{1}_{C,d+1}} \eta^{2}_{t} \right) \tag{31}$$

In both cases the close-to-close price change is linearly related to the lagged close-to-close price change in the other market and a first-order moving average error process.

3. The Many Markets Model

The model described above for the case of two markets may be generalised 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

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

where ΔS is a J×1 vector of price changes
η is a J×1 vector of news terms
A is a J×J matrix of the α_{ij} coefficients ($\alpha_{jj} = 0, \forall j$)
e is a J×1 vector of expectations of u held by agents in other markets

The solution to the signal extraction problem is

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

where Λ is a J×J diagonal matrix with λ_j as the j^{th} element of the leading diagonal

Combining (32) and (33) yields

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

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

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 and the rate of change of prices is indeterminate. The condition for multiple equilibria is that the matrix (I + B) is singular, and hence there is no unique solution for the rate of change of market prices. In conditions of a crash, for example, the β coefficients might rise to a level at which the matrix became singular. Secondly, 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 (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 is exogenous to the model being determined by time zone differences and local hours of trading.[7] In addition there are up to J jump points when markets re-open, and hence J(J-1) jumps in actual or shadow prices. When any market re-opens the accumulated value of the total news observed in that market is revealed to all other markets. At each jump point (when market j re-opens, for example) the jump in market i is equal to β_{ij} multiplied by the sum of η^j over the interval during which j has been closed. This holds true for all $i \neq j$. A convenient regression model is to take the close-to-open price change as the dependent variable. The independent variables in this specification are the changes during the trading day in the other markets prior to the opening of the dependent market. This procedure yields consistent estimates of the contagion coefficients. More efficient estimates can 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 (24) and (30)-(31) above. As the two market case demonstrates, the implications for estimation in this case depend upon the degree of overlap of trading in the various markets.

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[7] 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 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 paper.

4. 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% of total world market capitalisation.

4.1 Tests for Price Jumps

One of the features that distinguishes the contagion model from any fully revealing equilibrium model (such as the ICAPM) are the price jumps that occur in all markets whenever one market re-opens. For example, when New York opens there is a jump in the London price reflecting the information contained in the New York opening price. In the two-market case the size of the jump is given by equation (25). In fact, for the three main financial centres the impact 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 Wall Street; some US 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 Wall Street 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 Wall Street opens. Using data on the FTSE-100 Index in London we computed the volatility of 15-minute price changes throughout the trading day. Since there are considerable changes in the average level of volatility over the sample period intra-day volatility was calculated for three different sub-periods as shown in Figures 4 to 6.[8] Figure 4 shows the

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[8] The three sub-periods 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 13 October rather than 16

intra-day volatility during the pre-crash period (1 July to 13 October).[9] There are three times at which volatility is significantly higher than during the rest of the day, (i) 9.15-9.45 a.m., (ii) 11.15-11.45 a.m., and (iii) 2.15-3.15 p.m. The first of these periods coincides with 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 UK are announced. The third is the hour around the Wall Street open (which is at 2.30 p.m. London time). Note that this period is not one during which official US economic statistics are released. This occurs at 1.30 p.m. London time, and it is striking that there is a decline in volatility in London around this time suggesting that London reacts more to Wall Street's assessment of the statistics than to the news itself. Figure 4 appears to support the contagion model.

Figure 5 shows volatility in the sub-period from 1 December to end-February following the crash and its immediate aftermath.[10] 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 Wall Street. Again there is some support for the idea that London reacts to the opening price in New York. The size of this reaction in the sub-period including the crash and its aftermath is shown in Figure 6. 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 traders in 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 impact of Wall Street on London, as observed in Figure 6. These results are broadly supportive of the notion that the time around the Wall Street open is associated with unusually high volatility in London, although the response is more diffused than would be predicted by the

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October for the end of the pre-crash sub-period.

[9] We have excluded the observation for 11.30a.m.-12 noon on 20 August as it represents by far the largest single change in the sub-period (following an unexpected announcement of changes in interest rates) and distorts the graph.

[10] In this sub-period we have excluded the observation for 1.30-2.00p.m. on 10 December and 15 January which followed the announcement of US trade figures and are clear outliers.

simple theoretical model examined above.

4.2 Contemporaneous correlation between markets

To identify both the level of, and possible change in, the contagion coefficients we estimate the model on hourly data for stock price changes in New York, Tokyo, and London for the 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 shall 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 either to fundamentals in the conventional sense or to other sources of changes in equity values. If periods of high volatility exhibit little increase in economic "news", (for example, 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.

Of the three markets that we consider only London and New York have overlapping trading hours (see Figure 2). 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))

$$\Delta S_t^1 = \beta_{12}\ \Delta S_t^2 + (1-\beta_{12}\beta_{21})\eta_t^1 \qquad (35a)$$

$$\Delta S_t^2 = \beta_{21}\ \Delta S_t^1 + (1-\beta_{12}\beta_{21})\eta_t^2 \qquad (35b)$$

As we showed in section 2, the contagion coefficients β_{12} and β_{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 ICAPM. To see this consider the two-market ICAPM which implies that price changes obey

$$\Delta S_t^i = \beta_i \Delta S_t^W + \epsilon_t^i \qquad i=1,2 \qquad (36)$$

where ΔS_t^W is the percentage change in the world index

β_i is the normalised covariance with the world index

ϵ_t^i is the idiosyncratic component of the return

In the two-market case

$$\Delta S_t^W = w_1 \Delta S_t^1 + w_2 \Delta S_t^2 \qquad (37)$$

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

$$w_1\beta_1 + w_2\beta_2 = 1 \qquad (37)$$

From these equations it follows that

$$\Delta S_t^1 = \frac{\beta_1}{\beta_2}\Delta S_t^2 + \frac{\epsilon_t^1}{1-\beta_1 w_1} \qquad (39a)$$

$$\Delta S_t^2 = \frac{\beta_2}{\beta_1}\Delta S_t^1 + \frac{\epsilon_t^2}{1-\beta_2 w_2} \qquad (39b)$$

The difference between (35) and (39) is that the ICAPM implies a nonlinear restriction on the regression coefficients (in the two-market case this is that the product of the coefficients is unity). In the remaining empirical tests we focus on the change in the coefficients over time, and in particular their relationship with volatility. Whether these changes are more plausibly explained within a contagion model or in the ICAPM framework is a judgement 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 indices 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 US 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 19 October 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 20 October). 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.[11] In London 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.[12] For these reasons we re-calculated the correlation coefficient using the percentage change in (a) the S&P Futures price (quoted on the Chicago Mercantile Exchange) instead of the change in the Dow Jones Index, and (b) 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

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

[12] p.19, Quality of Markets Quarterly, Winter 1987-88, International Stock Exchange, London.

2, this produces a significantly higher correlation coefficient of 0.48 during the period 16 October to end-November, implying a substantial rise relative to the period before the crash, and even higher values during the crash week itself. All of the empirical results reported below are based on use of the futures index rather than the spot index for the US. It is also striking that the correlation between the two markets had fallen to approximately its pre-crash level by the beginning of 1988.

There was a significant increase in actual volatility during the week of the crash (see Figure 7) 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 8 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 pre-crash level.

Using the implied volatility measure we may test formally the hypothesis that the contagion coefficients are an increasing function of perceived volatility. When the price change in the other market is interacted with the value of implied volatility and added to the regression model implied by (35), there is striking evidence that the links between the two markets have indeed varied with changes in volatility.[13] 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 pre-crash mean of volatility (around 0.2), the response of both London and New York to a 1 per cent change in each 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 Wall Street 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.

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[13] The regressions include also the lagged dependent variable - see the discussion around equation (40) below.

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 prices (or, more, generally, returns) are serially correlated (Fama and French, 1986a, 1986b, and Poterba and Summers, 1987). This may arise through either variations in expected returns or a "catching-up" process, as described in fn.3, when investors in market i observe earlier periods' realisations of u^j. With serially correlated returns estimation of the following augmented version of equation (39) would provide a way of identifying the contagion coefficients

$$\Delta S_t^1 = \beta_{12}\,\Delta S_t^2 + \phi_1 \Delta S_{t-1}^1 + (1-\beta_{12}\beta_{21})\eta_t^1 \qquad (40a)$$

$$\Delta S_t^2 = \beta_{21}\,\Delta S_t^1 + \phi_2 \Delta S_{t-1}^2 + (1-\beta_{12}\beta_{21})\eta_t^2 \qquad (40b)$$

Serial dependencies in stock returns are notoriously unstable. When equation (40) was estimated using IV for the first and third sub-periods the coefficients were poorly determined. Table 3, therefore, presents both OLS and IV estimates of (40) for the sub-period that included the crash. The OLS estimates of the coefficients on lagged price changes are significantly different from zero at the 5% level, as are the IV estimates.[14] 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.

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[14] To allow for a possible "catching-up" process we tested for a more general dynamic specification of (40). But no higher order ARIMA process was significant.

4.3 Close-to-open changes in prices

The model determining the close-to-open price changes incorporating interactions between London and New York is described by equations (23) and (24). Table 5 presents estimates of the contagion coefficients based on this model. Rows 1, 2 and 3 show the estimates of equation (23) for the UK for the three sub-periods. 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 previous day from the close of London to the close of New York. Rows 4, 5 and 6 show estimates of equation (24) for the US for each of the sub-periods. 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 5 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 impact 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 impact 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 to 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 6. The contagion coefficient measuring the effect of market j on market i is denoted by β_{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 sub-periods. 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.

4.4 Serial Dependency in Returns and Portfolio Insurance

The role of portfolio insurance in the crash has attracted a great deal of attention in recent months. If it were the case that trading driven by portfolio insurance did lead to unnecessarily large price falls in New York then this "mistake" would be transmitted to other markets because, on the basis of past experience, it would be rational for market-makers in overseas equity markets to assume that the change in the US index contained news. Since portfolio insurance is only embryonic in the UK, a comparison of price behaviour in the US and UK may help to illuminate the importance of portfolio insurance.

Suppose that there are two types of investor; the first looks at "fundamentals" and the second sells as prices fall. When volatility is low portfolio insurers do not leave any detectable traces in price autocorrelations because the "rational" investors arbitrage them away. When volatility is high, however, we might expect to see some evidence of negative serial correlation, because "rational" investors may be reluctant to absorb the risk resulting from the transactions that would be necessary to eliminate the arbitrage opportunity.

To examine this issue we test for serial dependency in returns by regressing changes in stock prices on their own lagged values using hourly data for the UK and US. Of course, serial correlation of returns can arise for reasons other than behaviour of the stop-loss order type. First, infrequent trading can lead to positive serial correlation. Except for the crash week, however, this is unlikely to be significant because the indices that we use reflect price movements in very large, frequently traded, companies. And for the crash week itself we use prices from the futures market. Second, it can be argued that negative serial correlation might arise if the data are for transactions prices, as it is likely that transactions alternate between purchases and sales by market-makers. In this study, however, we use indices based on mid-market prices. Third, mean reversion in stock prices may induce negative serial correlation, but the usual story for such behaviour is not relevant for such high frequency data. Moreover, the mean reversion explanation does not lead us to expect an increase in the degree of negative serial correlation when volatility rises.

The results on serial dependency are presented in Table 6. The regressions for the US and UK spot prices and for the UK futures price all suggest that the degree to which returns exhibited negative serial correlation increased significantly during the week of the crash, as shown by the interaction between lagged returns and the dummy variable DUM which takes the value unity during the crash week and zero for all other observations. The exception is the regression which uses data for the US futures index during the crash week. Behaviour of the kind "sell when prices fall, buy when prices rise" appears to have had a bigger effect on share prices in London, despite the fact that portfolio insurance as such is relatively unimportant in the UK. We conclude that such time-honoured practices as stop-loss orders had as significant an effect on share prices as formal dynamic hedging strategies.

5. 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 U.S. 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 paper 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 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.

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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

Table 2

CORRELATION BETWEEN LONDON AND NEW YORK STOCK MARKETS

(hourly data for overlapping trading hours)

	Variant	Sample Period	Correlation Coefficient	Number of Observations
1.	Share Price Indices	1 July - 16 October, 1987	0.270	191
2.	Share Price Indices	19 October - 30 November, 1987	0.379	86
3.	Futures Data for US	19 October - 30 November, 1987	0.478	84
4.	Futures Data for US	1 December 1987 - 28 February 1988	0.194	175
5.	Futures Data for US	Crash Week	0.649	10
6.	Futures Data for both markets	Crash Week	0.750	10

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	β_{12}	ϕ_1	β_{21}	ϕ_2	VOL*β_{21}	VOL*ϕ_2	Number of Observations	R^2	D.W
New York	1 Jul - 28 Feb	OLS	-	-	-0.46	0.65	3.54	-1.06	316	0.588	1.93
					(-1.82)	(5.90)	(7.86)	(-5.00)			
London	1 Jul - 28 Feb	OLS	-0.07	0.01	-	-	0.94	-	316	0.516	1.98
			(-0.68)	(0.35)	-	-	(4.05)			-	-
New York	19 Oct - 30 Nov	OLS	-	-	1.56	0.16	-	-	60	0.644	1.81
					(9.14)	(2.05)					
London	19 Oct - 30 Nov	OLS	0.36	-0.09	-	-	-	-	60	0.628	1.80
			(9.22)	(-1.25)	-	-	-	-			
New York	19 Oct - 30 Nov	IV	-	-	2.16	0.09		-	60	0.568	1.74
			-	-	(6.35)	(1.02)					
London	19 Oct - 30 Nov	IV	0.41	-0.08	-	-		-	60	0.620	1.74
			(6.43)	(-0.98)							

Table 4

ESTIMATES OF THE CONTAGION COEFFICIENTS BETWEEN LONDON AND NEW YORK WITH TIME ZONE TRADING

(t - values in parentheses)

	Sample Period	β_{12}	β_{21}	Number of Observations	R^2	D.W.
1. UK	1 July - 18 October	0.21	-	59	0.159	1.85
(Equation 23)		(3.28)				
2. UK	14 October - 30 November	0.39	-	29	0.576	2.80
(Equation 23)		(6.06)				
3. UK	1 December - 28 February	0.36	-	56	0.486	1.89
(Equation 23)		(7.14)				
4. US	1 July - 13 October	-0.09	0.18	59	0.122	1.96
(Equation 24)		(-0.23)	(2.69)			
5. US	14 October - 30 November	0.57	1.11	29	0.494	2.44
(Equation 24)		(4.23)	(4.81)			
6. US	1 December - 28 February	0.53	0.44	56	0.425	2.02
(Equation 24		(3.85)	(6.00)			

Table 5

ESTIMATES OF THE CONTAGION COEFFICENTS BETWEEN JAPAN, UK AND US WITH TIME ZONE TRADING

(t - values in parentheses)

Regression	Sample	β_{ij}	$\beta_{ij}\beta_{ji}$	Number of Observations
London on Japan	1 July - 13 October	0.19	0.01	67
		(3.31)	(0.04)	
London on Japan	14 October - 30 November	0.58	-0.46	31
		(7.33)	(-2.88)	
London on Japan	1 December - 28 February	0.06	-0.06	58
		(0.92)	(0.46)	
Japan on London	1 July - 13 October	0.17	0.12	66
		(1.26)	(1.00)	
Japan on London	14 October - 30 November	0.26	-0.49	31
		(1.60)	(-3.23)	
Japan on London	1 December - 28 February	0.16	-0.34	58
		(1.22)	(-2.73)	
US on Japan	1 July - 13 October	0.08	-0.19	71
		(1.38)	(-1.58)	
US on Japan	14 October - 30 November	0.16	-0.12	32
		(1.28)	(-0.67)	
US on Japan	1 December - 28 February	0.04	0.09	59
		(0.60)	(0.66)	
Japan on US	1 July - 13 October	0.20	0.25	70
		(1.93)	(2.13)	
Japan on US	14 October - 30 November	0.49	-0.56	32
		(7.13)	(-3.72)	
Japan on US	1 December - 28 February	0.11	-0.20	59
		(1.12)	(-1.56)	

Table 6

SERIAL DEPENDENCIES IN STOCK RETURNS

	Dependent Variable ΔS_t			
Independent Variable	UK	UK Futures	US	US Futures
ΔS_{t-1}	0.12	0.09	-0.09	-0.09
	(2.75)	(1.62)	(-1.79)	(-1.30)
DUM (ΔS_{t-1})	-0.17	-0.31	-0.36	0.14
	(-2.77)	(-4.70)	(-5.06)	(1.80)
T	1138	975	973	977
R^2	0.008	0.035	0.083	0.004

Note:- All regressions include a constant term.

Figure 1

STOCK MARKET INDICES, OCTOBER 1987

1 October 1987 = 100

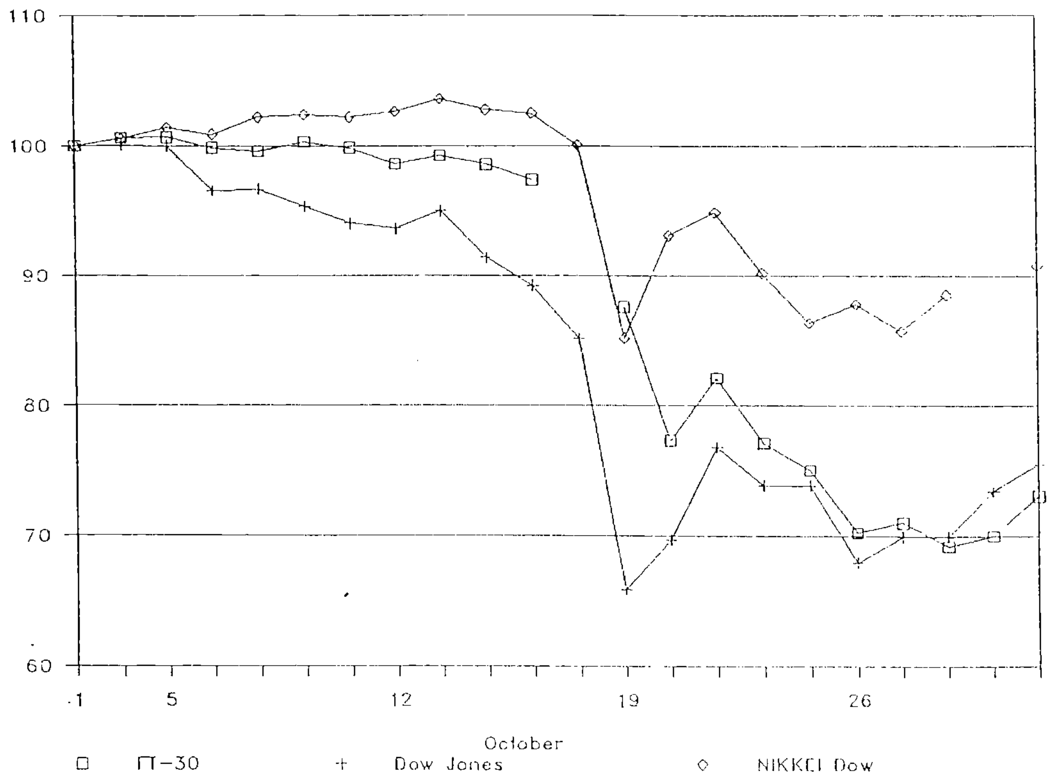

Figure 2

Trading Hours, London, New York and Tokyo, GMT

(winter time)

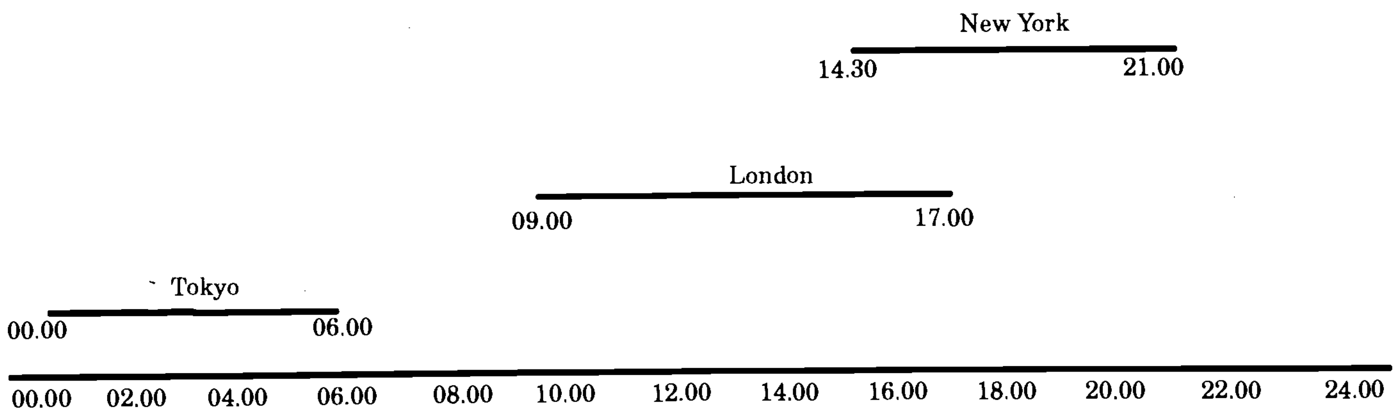

Figure 3

TIME ZONE TRADING WITH TWO MARKETS

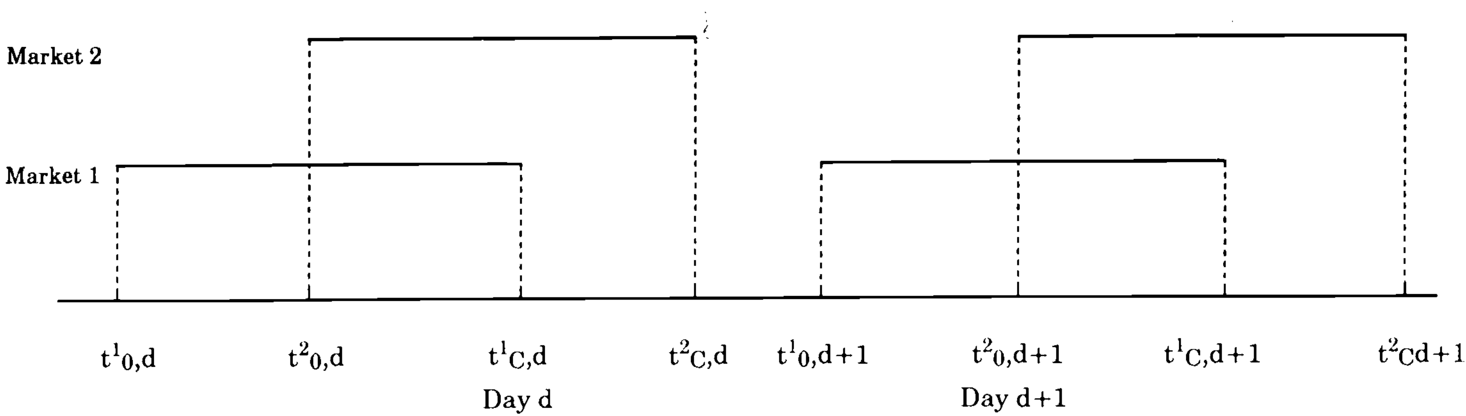

Figure 4

INTRA-DAY VOLATILITY IN LONDON

(1 July to 13 October 1987)

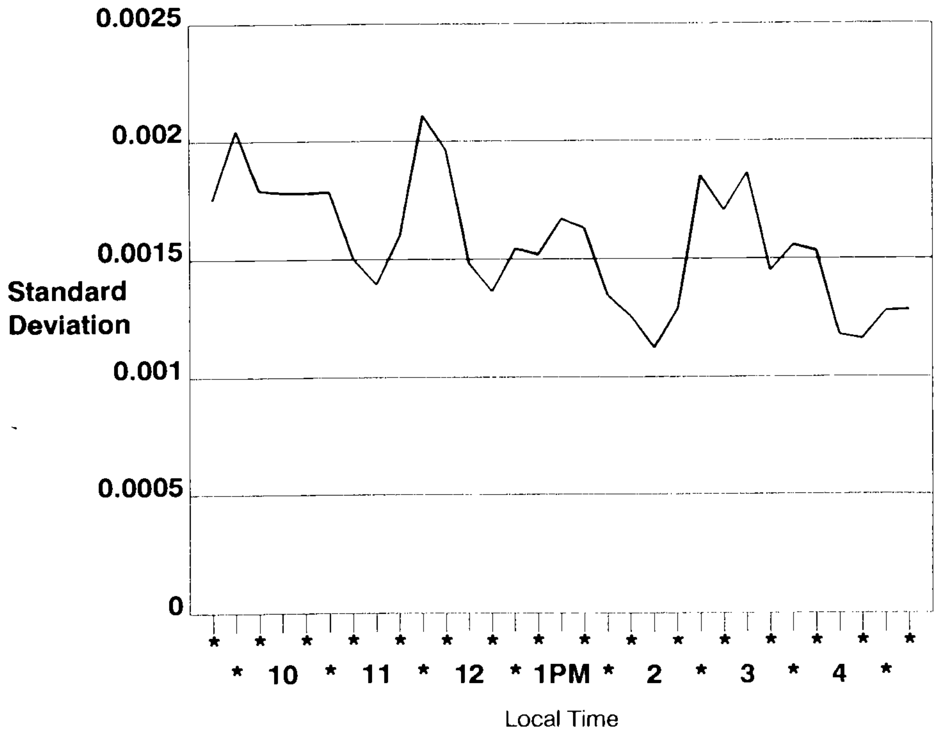

Figure 5

INTRA-DAY VOLATILITY IN LONDON

(1 December 1987 to 26 February 1988)

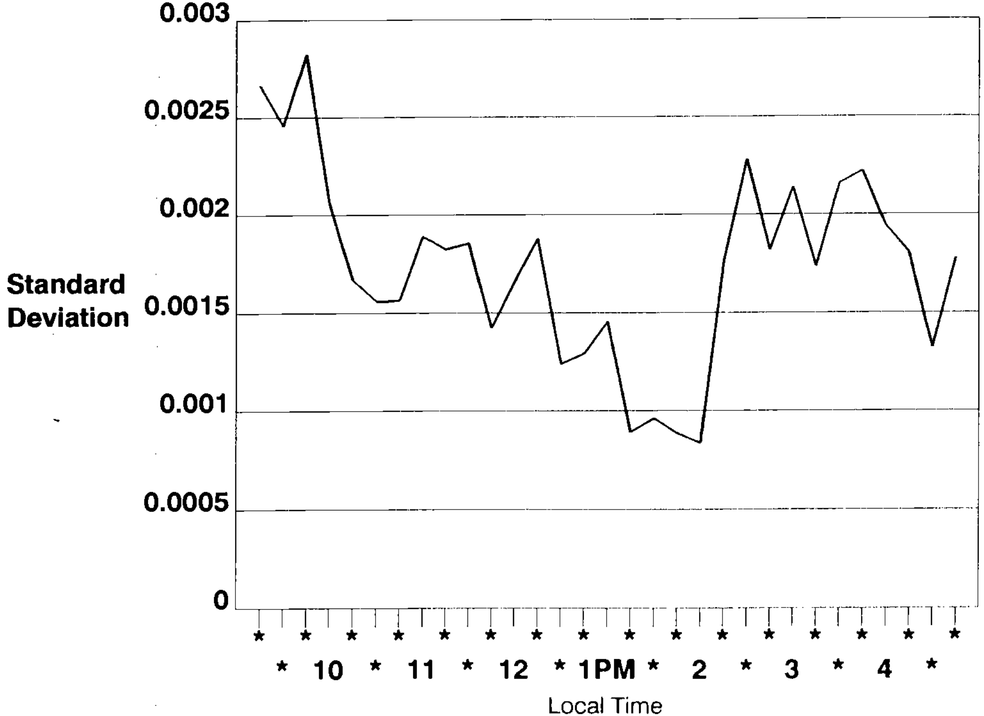

Figure 6

INTRA-DAY VOLATILITY IN LONDON

(14 October to 30 November 1982)

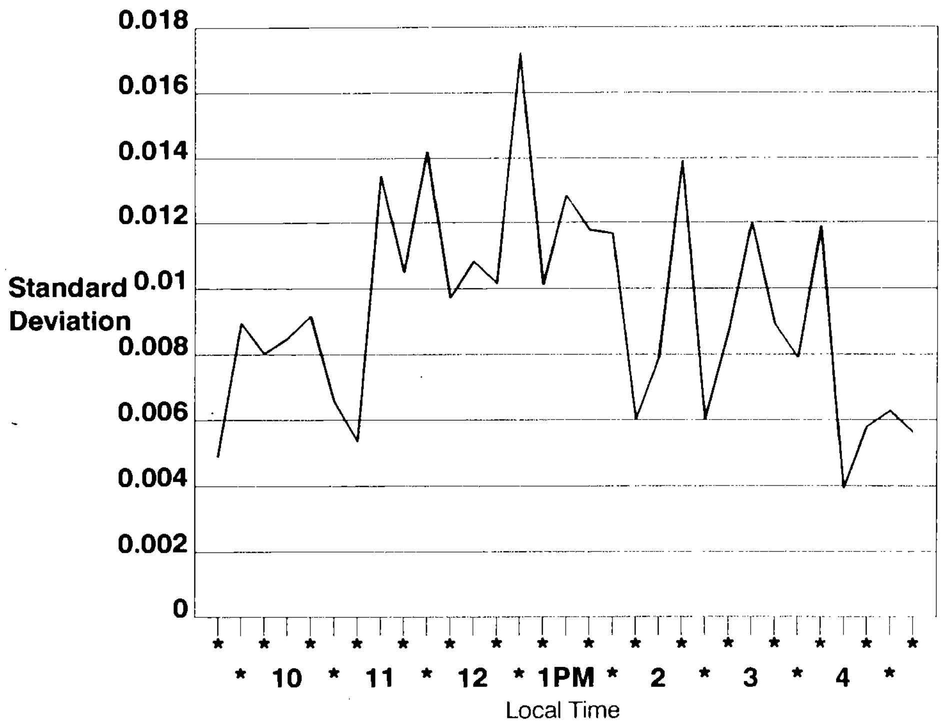

Figure 7

VOLATILITY IN NEW YORK AND LONDON

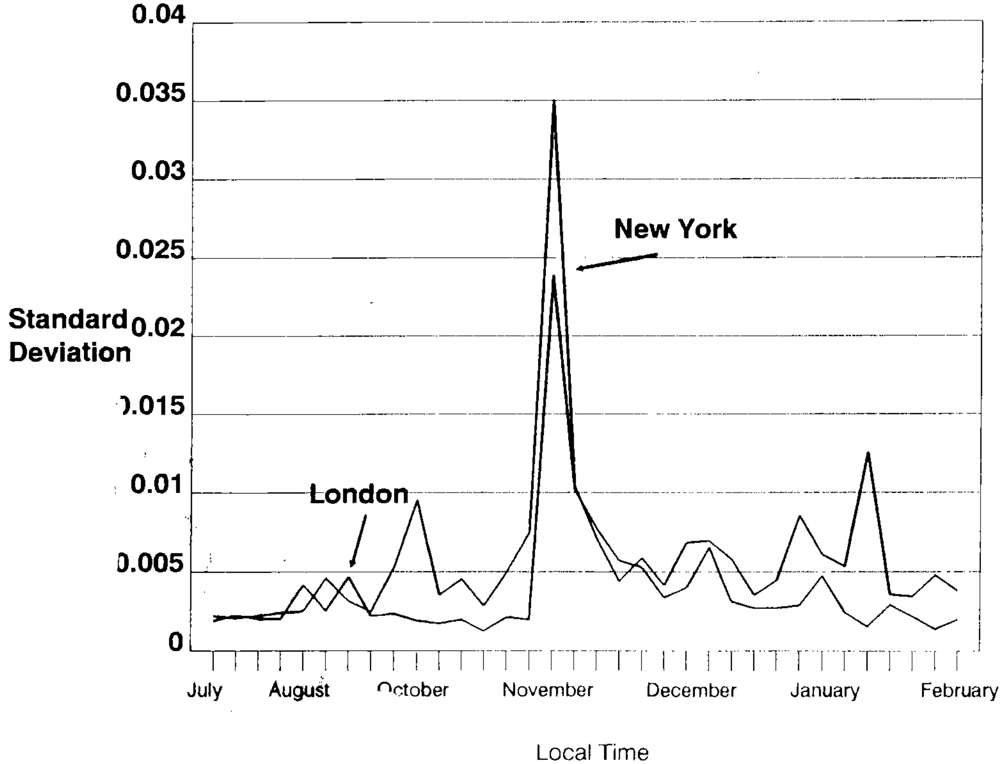

Figure 8

Alternative measures of volatility, London