Information Dispersal: A Microstructure Analysis of Stock Index Futures Volatility Patterns

Robert T. Daigler and Anthony F. Herbst

Robert T. Daigler
Department of Finance BA 206
College of Business
Florida International University
Miami, Florida 33199

305-348-3325
E-mail: DAIGLERR@FIU.EDU

Anthony F. Herbst
Department of Finance
College of Business
University of Texas, El Paso
El Paso, Texas 79968-0543

915-747-7791
E-mail: AHERBST@UTEP.EDU

Robert Daigler is Associate Professor of Finance at Florida International University and was a Visiting Scholar, Graduate School of Business, Stanford University during the research phase of this paper.

Anthony Herbst is Professor of Finance and holds the Charles R. and Dorothy S. Carter Chair in Business Administration at the University of Texas at El Paso.

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Abstract

The relationship between information and volatility has received considerable attention in the literature. This paper studies information by applying a different methodology, cross-spectral analysis, to the transmission of volatility between markets. Cross-spectral analyzes the strength of the relationships and the lead-lag characteristics between stock index futures volatility measures for high frequency intraday futures volatility data. The use of futures avoids the difficulties inherent in cash index values, as well as providing reliable microstructure data for volatility measures. Open, high, low, and closing prices for each three minute time interval are employed to calculate Garman-Klass volatility values for the S&P 500, MMI, and NYSE futures contracts in order to examine the transmission of volatility. Three theories concerning the transmission of information are examined with this data: the dominant market theory, the pure information theory, and the independent markets theory. The results show an information transfer in volatility between the futures instruments such that the dominant market theory is valid for a large number of cases.

I. Introduction

Volatility is an important measure of the flow of information. Models by Ross (1989) and Bookstaber and Pomerantz (1989) show that the information-volatility relationship is more important than the information-price change relationship. In addition, option prices, portfolio insurance strategies, and other financial models are directly related to volatility, while the direction of information flow and market volatility across markets is of interest to traders of due to possible lead-lag volatility relationships.

The examination of the time series properties of volatility within a single financial market series has received attention via the application of GARCH.[1] Another approach is to study volatility transmission between locations (particularly for currencies and international stock indices) and between stock index futures and cash indices. For example, Engle, Ito and Lin (1990) examine currency volatility transmission by applying GARCH methodology to the daily open and close yen/dollar spot rate in Tokyo, London, and New York. They conclude that volatility is transmitted from one location to another (volatility acts like a "meteor shower"), rather than volatility only occurring in one location (a "heat wave"). Najand, Rahman, and Yung (1992) use daily currency

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[1] Several hypotheses exist concerning how information is processed and how GARCH (generalized autoregressive conditional heteoscedasticity) effects develop in high frequency intraday data for a single series. One hypothesis is that the amount or quality of information reaches the marketplace in clusters. A second hypothesis is that the time it takes traders to process the information causes trading in clusters. See Diebold and Nerlove (1989) and Gallant, Hsieh, and Tauchen (1989). See Bollerslev, Chou and Kroner (1990) for an extensive review of the literature.

futures data to show that volatility in one currency futures contract is transmitted to other currency futures, although the pattern is very diverse.

Studies of the transmission of volatility among international stock markets examine volatility spillovers from one market to another. Eun and Shim (1989) use daily prices, Hamao, Masulis, and Ng (1990) and Lin, Engle and Ito (1994) use daily open and closing prices, and King and Wadhwani (1990) use hourly prices around the 1987 crash to validate volatility spillovers among these markets.[2]

Stock index futures versus cash index volatility provide higher frequency data to examine volatility transmission. Cheung and Ng (1990) use 15 minute quotes for the S&P 500 contract to find that futures volatility leads cash market volatility in the first 15 minutes of trading. Chan, Chan and Karolyi (1991) use 5 minute prices for the S&P 500 and MMI contracts and find that volatility changes in the respective futures (cash) market predict changes in the cash (futures) market i.e. the relationship goes in both directions. Kawaller, Koch, and Koch (1990) calculate 30-minute volatility measures based on minute-to-minute price changes for the S&P 500 futures and cash markets. They find no robust systematic pattern of futures volatility leading cash market volatility, or vice-versa, by using Granger causality tests. Therefore, sometimes futures lead cash volatility, while other times cash lead futures or no lead relationship exists.[3]

Overall, the currency and international stock market studies show that volatility does spill over from one market to another. However, the lack of high-frequency intraday data and the differing trading hours among the various spot currency and international stock markets create difficulties in examining volatility lead-lag structures and the process of information transfer. The stock index futures/cash market studies do provide intraday evidence of volatility transmission between these markets, but the direction and strength of this relationship changes. Moreover, the stale prices inherent in cash index data makes definitive conclusions difficult.

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[2] Other articles of interest concerning the degree of interrelatedness of international equity markets on a daily basis, as well as the direction and magnitude of the transmission of these market movements, include Fisher and Palasvirta (1990), Philippatos, Christofi and Christofi (1983), and Hilliard (1979).

[3] Thus, while futures price changes lead cash changes, Chan, Chan and Karolyi (1991) and Kawaller, Koch, and Koch (1990) show that the volatility relationship can go in either direction.

The purpose of this paper is to apply a different methodology, cross-spectral analysis, to the study of the transmission of volatility between markets. This is accomplished by examining the strength of the relationship and the lead-lag characteristics of the information processing relationships by employing cross-spectral analysis between three stock index futures contracts for three minute interval measures of volatility.[4] The three stock index futures studied here are the S&P 500, MMI, and NYSE contracts. Using futures markets avoids the non-trading difficulties with cash indices, since futures trade prices immediately reflect market sentiment. Moreover, the number of trades available for futures contracts allow the high-frequency measures of volatility, which provides more precise analysis than other studies which employ 15 and 30 minute intervals.[5] While the MMI contract currently has very low volume, this contract had sufficient transactions during the period of analysis to obtain valid conclusions concerning the transmission of volatility.

The empirical evidence in this paper shows that information flow from one market to another, as evidenced in volatility measures, does occur between stock index futures for a large majority of cases. Hence, the dominant market theory, i.e. where information initially becomes known in one market and then passed to other markets, is strongly supported by the evidence.

II. Methodology

Cross-spectral analysis allows an examination of the existence, strength, and lead-lag relationships between time series when the time interval identifying the cycle or the lead-lag

[4] One minute time intervals often have few transactions per minute for the lower liquidity stock index contracts. This problem with liquidity created difficulty for the measure of volatility employed, therefore three minute intervals are used here. Originally the Value Line contract also was examined. However, a lack of liquidity for most of the months analyzed adversely affected the interpretation of the results.

[5] Spot indices impound serial correlation into the data due to less frequent trading of smaller capitalization issues. This serial correlation from the smoothing effect of using "old" prices results in downwardly biased volatility estimates for the cash indices. Thus, the futures transactions data provide a more accurate high frequency measure of volatility than available for the cash indices. Cheung and Ng (1990), Herbst and Maberly (1987), Herbst, McCormack and West (1987), and Kawaller, Koch, and Koch (1987), among others, show that futures price changes lead cash stock indices price changes by 15 to 30 minutes.

component is not known a priori.[6] In turn, high-frequency, liquid futures volatility data allow examination of the pattern of information flow. Three theories concerning information flow are examined here:[7]

- Dominant market theory: information initially flows into the market that reacts the fastest to news. Thus, a market with the greatest liquidity and lowest transactions costs, including the lowest bid-ask spreads, can be a dominant market. Alternatively, a market where certain traders have asymmetric information causes that market to be more sensitive to information, creating a dominant market.

  The S&P 500 futures contract has substantial liquidity and lower bid-ask spreads than other stock index futures markets. This liquidity also attracts program trading. Volatility would then flow to the other markets. Alternatively, asymmetric information and knowledge of the activity of major stocks could have a greater initial effect on the MMI futures.[8]

- Pure information theory: information is reflected in <u>all</u> markets at the same time, as traders use all markets immediately upon receiving market information in order to maximize profits.

  All public information reaches each trading floor at the same time via electronic news and/or traders placing orders. Ederington and Lee (1993) show that economic news is the major

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[6] Identification of volatility cycles and the transmission of futures price volatility may be indicative of the physical characteristics of information creation and dispersal as well as the rates at which electronic information queues can be loaded and unloaded when constrained by human factors. Therefore, regular waves in volatility need not imply exploitable market inefficiency, particularly if the amplitude of the waves is small relative to random price movements in the price. Alternatively, relationships may not be apparent on normal market days, but may become evident in active periods. Although the exchanges that trade the index futures contracts in this study are in different physical locations, modern electronic communications diminish the adverse effects of location as a factor in information transfer. The choice of three minute intervals for this study is based on the belief that information is transmitted quickly.

[7] See the following for discussions of information theory and informed trader models: Admati (1991), Admati and Pfleiderer (1988-89), Bookstaber and Pomerantz (1989), French and Roll (1986), Kyle (1985), and Ross (1989).

[8] An example of a dominant market is shown by Blume, MacKinlay and Terker (1989), who found that the S&P 500 stocks fell 7% more than non-S&P 500 stocks on October 19, 1987. They attributed the difference to order imbalances. Another factor affecting volatility relationships is the composition of the underlying stock indices (the Blume, MacKinlay and Terker findings are related to this composition issue). Hence, institutional interest in the S&P 500 contract, and the resultant transmission of information via arbitrage and program trading activity (in association with the liquidity of the S&P 500 futures) would make this contract a dominant market.

factor affecting volatility spikes in interest rate and currency futures contracts. Such macroeconomic news could then be transmitted instantaneously to all futures markets, with trades instituted by speculators, floor traders, and program traders.

- Independent markets theory: volatility in one futures market is independent of the volatility in other markets. This theory is consistent with the "noise" aspect of trading discussed in Admati and Pfleiderer (1988-89), French and Roll (1986), and Kyle (1985).

  Speculators and hedgers in the individual futures markets dominate the volatility behavior of each market, such that information (volatility) is <u>not</u> passed from one market to another.

Cross-spectral analysis provides measures of time-dependent relationships between time series. While spectral analysis provides a frequency domain analog to autocorrelation, cross-spectral analysis provides an analog to cross-correlation analysis in the time domain. The single series spectrum reveals any regular rhythms, pulses, or cycles contained in the data, with the cross-spectrum disclosing such wave propagation <u>between</u> time series data.[9]

The principal measures of relevance in cross-spectral analysis are coherence, phase, and gain; these measures are formally defined in the Appendix. Coherence measures the relationship between cycles of the same frequency in two time series. Thus, coherence is interpreted as a coefficient of determination.[10] Zero coherences at all frequencies, as tested statistically, means no association between the two time series exists. Phase measures the shift of a cycle of a given frequency in one series vis-à-vis the second series, and consequently reveals the lead-lag relationship for that <u>particular</u> frequency. The phase $\phi(\alpha)$ of a cycle ranges from $-\pi$ to π degrees. If a complete cycle (period) is 10 minutes in length then a phase of $\phi(\alpha) = .5\pi$ means that the first series leads the second by approximately 2 1/2 minutes, i.e. (1/2) x 10 x $.5\pi/\pi$. For $\phi(\alpha) = -.5\pi$ then the second series leads the first by 2 1/2 minutes (negative values refer to a lead by the second

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[9] Spectral analysis decomposes the data into Fourier series. Fourier coefficients bear a strict relationship to the sample variance of the original series. Thus, the use of the Fourier series allows a type of analysis of variance of the original series.

[10] Terminology differs among those who explain/use spectral analysis. For example, our definition of coherence is called squared coherence by others. Coherency is also employed as a synonym for coherence. Therefore, the values reported here would be larger if the term coherence was used as the equivalent of correlation and coherence squared was used as the equivalent of the coefficient of determination.

series). More generally, the lead of a series is computed as (.5 period X phase)/π. Gain measures the strength of a cycle of the same period in the dependent series relative to the independent series, that is, whether the strength is amplified or diminished. The gain corresponds to the coefficient of the X variable in regression analysis.

Spectrum estimates are converted to time domain measures for reader convenience. A frequency of 0.1 cycles per minute in the frequency domain translates to a period of 10 minutes in the time domain.[11] Spectral and cross-spectral analysis are best applied to stationary time series data. If the data are nonstationary then the high power results are concentrated at the lower frequencies (longer time periods), while no power appears at the higher frequencies (shorter time periods). The data in this study are detrended and a high pass filter technique is employed to remove any emphasis on the longer time periods caused by nonstationarity. The results bear out the success of this standard technique.[12]

Statistical hypotheses which associate the cross-spectral results to the theories relating information flow to volatility are as follows:

- Hypothesis 1: A high coherence with a significant phase supports the dominant information theory.
- Hypothesis 2: A high coherence with a zero phase (no lead-lag effect) supports the pure information theory.

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[11] The computer implementation of the spectral methodology works in the frequency domain, which is the normal realm of communications engineers and scientists. The time dimension is more appropriate for financial economics data.

[12] Each data series is "padded" to a length of 8192 and "tapered" to achieve both maximum computational efficiency and comparative uniformity of the results. Padding is necessary because the fast Fourier transform (FFT) algorithm used to analyze the data is most efficient when the data series contains a number of observations that is an integer power of 2 (2^{13} is 8192). Padding is accomplished by appending zeros to the end of the data series. Tapering is performed in order to reduce bias in the spectral estimates whenever padding is done and is a standard adjustment for spectral analysis. Since the cross-spectral analysis examines relationships <u>across</u> markets for <u>adjacent time intervals</u>, and each series is comprised of an equivalent number of non-zero observations for any given month, the important criteria is that the data match in the timing of their observations. Thus, adding additional observations for padding purposes does not affect this timing relationship nor does it adversely affect the results. Brillinger (1975) explains both techniques in depth, and the BMDP Statistical Software Manual, Vol. 2 (1990) summarizes the procedure for tapering. For the sake of brevity, and because it is not central to this research, that material is not repeated here.

- Hypothesis 3: Insignificant coherences support the independent markets theory.

III. Data

The five most volatile months since the initiation of stock index futures, namely April, October, November, and December 1987, and January 1988 are selected to examine volatility transmission across stock index futures. For comparison, the two average volatility months of July and November 1986 are chosen from the months with median volatility during the same time period.[13]

Three minute time intervals are generated from the time and sales records of the S&P 500, MMI, and NYSE futures contracts for each day of the seven months chosen. Each time interval employs its open, high, low, and close price for each contract to generate Garman-Klass (1980) volatility measures. This measure is seven times more efficient than using the typical close-to-close between intervals.[14] The Garman-Klass volatility measure is defined by:

$$Var(GK) = 1/2\,[\ln(High) - \ln(Low)]^2 - [2\ln(2) - 1]\,[\ln(Open) - \ln(Close)]^2 \qquad (1)$$

Table 1 provides summary statistics on the data by month - including the means of the time interval Garman-Klass volatilities, the standard deviations of the volatility measures, the maximum values of the volatilities, and the means of the number of ticks (price changes) per time interval. Note that the S&P 500 contract has a (measured) mean volatility that is typically greater than the

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[13] The most active futures contracts are employed in the analysis. The most active contract for the S&P 500 and NYSE contracts was always the nearby expiration, except the December 1987 contact when the first deferred became the most active for five trading days before the nearby expired. The MMI nearby expires each month. The nearby MMI contract is most active up to and including the last day it is traded; therefore, the current nearby MMI contract is always employed in the analysis. The choice of the months employed, especially the two average volatility months, was constrained by the requirement that the Major Market Index was liquid. August 1984 was the fourth most volatile month, but the MMI contract was not active. The MMI also became less active starting in the 1990s. Also, prior to padding (explained above), the number of actual time intervals varies because several days are missing from the database, the market closed early after the October 1987 crash (which carried into November 1987), and the number of trading days varies across months. The first 15 minutes of the MMI contract, which trades before the cash markets open, is omitted from the data.

[14] Wiggins (1992) shows that the Garman-Klass estimator is only slightly downwardly biased, and is significantly more efficient than using close-to-close data.

other contracts, but the S&P 500 often has a lower standard deviation of volatility. The S&P 500 contract also has a much larger number of ticks, showing it to be the most active contract. The smaller number of ticks for the other contracts suggests that the high and low prices are biased toward the mean, creating a smaller mean volatility for these contracts than would be measured if a larger number of ticks were available.

One minute time intervals also were examined for cross-spectral relationships. However, 36.5% of the MMI one-minute intervals and 27.7% of the NYSE intervals only had 0 or 1 tick (price change). Moreover, three months of the MMI contract had over 50% of the intervals with only 0 or 1 tick. Since the Garman-Klass measure needs at least two observations to generate a positive measure of volatility, the one minute time interval was inappropriate for our purpose.

[SEE TABLE 1]

IV. Coherence and Phase Results

Table 2 shows the peak coherences and the associated F-values, and periods, using "All Periods" (frequencies) and for "Periods Less than 20 Minutes."[15] Hypotheses 1 to 3 from Part II can be tested by examining whether the peak coherences are statistically different from zero for each of the seven contract months and the three contract pairings. Thus, testing the peak coherences determines whether a volatility relationship exists between the stock index futures contracts.

Fisher and Palasvirta (1990) employ a simulation procedure to show that testing the peak coherence does not create biased results. Moreover, the confidence interval results reported below support the significance of the peak coherences. To test the significance of the peak coherences one employs the test statistic, Y, which is calculated as:

$$Y = \frac{2m \left|\Re_{XY}(\alpha)\right|^2}{\left[1 - \left|\Re_{XY}(\alpha)\right|^2\right]} \tag{2}$$

[15] In each case there are 172 frequencies (periods) for which the cross-spectral measures are computed. The number of frequencies is a function of the bandwidth, which is explained below, and the number of observations. The narrower the bandwidth, the greater the number of frequencies. The fewer the observations, the less the number of frequencies. Spectral methods are robust to outliers (see Reinmuth and Geurts (1977)). The October 1987 data possess outliers for the volatility measure.

where $\Re$ represents the coherence between series X and series Y at frequency α, and m denotes the window width; $m = N B_W/\pi$, with N equaling the number of observations, and B_W is the bandwidth used, $B_W = 0.0171$. According to Brockwell and Davis (1991), the coherence is distributed as the square of the multiple correlation coefficient, and thus Y ~ F(2, 4m) under the hypothesis $|\Re_{XY}(\alpha)| = 0$.[16]

[SEE TABLE 2]

The resultant F-values from (2) in Table 2 strongly reject Hypothesis 3, since the null hypothesis that the peak coherence equals zero at the 0.005 level is rejected for 41 of the 42 cases. Moreover, these coherences are consistently high, typically over .60. These strong results exist both for the "All Periods" and "Less than 20 Minutes" columns, showing that the results are not dependent on synchronization of cycles in the "longer-term."

Table 3 provides the related phases (in radians), leads (in minutes), and gains for the three minute intervals. Leads are not given if the related coherence is insignificant. A positive phase means that the first series leads, while a negative phase means the second series leads. Equation (3) provides the confidence interval for the phase:[17]

$$\Phi_{XY}(\alpha) \pm \arcsin \{[(1 - \Re_{XY}^2(\alpha))/\Re_{XY}^2(\alpha)]\ [2F/(\upsilon-2)]\}^{1/2} \qquad (3)$$

Where: Φ_{XY} = the calculated phase between series X and Y (measured in degrees)

α = the frequency (period)

υ = the degrees of freedom = N/P where N is the number of observations and P is the period length

$F_{2,\,\upsilon-2}$ = the F-value with 2 and υ - 2 degrees of freedom.

[SEE TABLE 3]

Thirteen of the 21 cases for "All Periods" have significant phases, while 15 of the 20 phases for "Less than 20 Minutes" are significant. The resultant leads are less then 1.1 minutes in all

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[16] The proper choice of the bandwidth filters out most of the spurious effects of random shocks; specifically, it determines the width of the window for computing the average of the periodogram for the frequency of the spectral analysis. The bandwidth was selected by using the narrowest bandwidth for which the spectral functions ceased being smooth, a standard procedure termed "window closing" that is recommended by Jenkins and Watts (1968).

[17] See Jenkins and Watts (1968, p. 437).

cases, while the maximum possible lead for a 20 minute cycle would be 10 minutes.[18] All results are converted from three minute periods to minutes for easy comparison. The results in Tables 2 and 3 strongly reject the independent markets theory, since the coherences are highly significant. The dominant market theory receives the most support, since 75% of the shorter-period cases possess significant phases.

The gain, or "power" (as given in equation [A9]), is equivalent to a regression coefficient between the independent series X and the dependent series Y using cycles of the length of the period of the cross-spectral analysis. Thus, the gain determines the extent that Y magnifies the effect of X. If the stock index futures volatilities are similar for a given period, which is a plausible assumption, then the gains would be near one. The actual gains shown in Table 3 are relatively close to one, with the exception of October 1987, supporting the use of the three minute time interval as providing adequate information on the relative volatilities.

IV. Coherence Diagrams

The purposes of cross-spectral analysis are to identify the periods (frequencies) when the two series have a high degree of association, i.e. coherence, and to identify any possible phase shift of these series. When significant relationships exist they typically will occur only at several periods, not at the majority of periods.

Some applications have created confusion concerning the "typical" number of periods possessing significant coherences. In particular, employing cross-spectral coherence diagrams involves a tradeoff between finding clearly identifiable periods of peak coherences versus generating "smooth" coherence diagrams. The larger the size of the "window," the smoother the coherence diagrams. Some authors advocate windows using up to 40% of the observations to produce a smooth diagram. Conversely, we employ a narrow window to emphasize the peak coherences, with the results that the coherence diagrams look more "choppy" than other spectral applications in Finance and Business. Thus, the objective of our cross-spectral analysis is to find

[18] In theory, the phases are transitive, i.e. if A leads B by three minutes and B leads C by two minutes then A will lead C by five minutes. The phase values in Table 3 are not comparable since the periods of peak coherences differ from one pair to the next. Moreover, statistical fitting of the cycles also would affect the pure transitivity of the results.

some periods possessing significant large coherences rather than many periods having lower coherences.

V. Summary and Conclusions

This paper examines volatility transmission across stock index futures contracts using volatility measures for three minute time intervals. Employing liquid futures contracts creates fewer difficulties than comparing stock index futures data to the "old" cash stock index value. Cross-spectral analysis provides a unique technique to examine time based relationships between these series.

The cross-spectral analysis of the three minute intervals provides very significant coherences with a large majority of significant phases. The associated leads are typically less than one minute. The results support the dominant market theory of information transfer. No support is provided for the independent markets theory. the short lead times associated with the shorter time periods suggest that studies employ short interval or transactions data for volatility studies, rather than the 15 to 30 minute intervals employed in previous studies on price changes. To the extent that some instability of the results does exist, it is similar to the change in direction and strength of the stock index/cash market lead-lag volatility relationships found by Kawaller, Koch, and Koch (1990) and other researchers.

The results and conclusions here have implications for other markets. Does information (volatility) in the cash currency market move from one location to another in a similar manner to stock index futures volatility? Does the volatility flow from options markets to futures/cash markets or vice-versa? Is there an information flow between interest rate and stock index futures markets? Further research in this area of information/volatility flow should provide interesting results.

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APPENDIX

The Fourier transform on which spectral analysis is based is defined in complex terms (which is equivalent to an alternative definition using the cosine) as

$$Z_x(\omega) = \sum_t X(t)\exp(-2\pi i\omega t) \tag{A1}$$

where i is defined as $i^2 = -1$, and X(t), with t = 0, 1, 2, ... , T-1 denotes the time series to be transformed, and where ω is the frequency.

The transform yields real and imaginary parts for Z, denoted by A and B.

$$\begin{aligned} A_x(\omega_k) &= \sum_t X(t)\cos(2\pi\omega_k t) \\ B_x(\omega_k) &= \sum_t X(t)\sin(2\pi\omega_k t) \end{aligned} \tag{A2}$$

From the A and B terms of the transforms of two time series, X(t) and Y(t) the periodogram of each, and the cross-periodogram are defined by

$$\begin{aligned} I_{XX} &= \frac{|Z_X(\omega_k)|^2}{T} = \frac{(A_x(\omega_k)^2 + B_x(\omega_k)^2)}{T} \\ I_{YY} &= \frac{|Z_Y(\omega_k)|^2}{T} = \frac{(A_y(\omega_k)^2 + B_y(\omega_k)^2)}{T} \end{aligned} \tag{A3}$$

$$\begin{aligned} I_{XY} &= \frac{(Z_Y(\omega_k)\overline{Z_X(\omega_k)})}{T} \\ &= \frac{(A_Y(\omega_k)\,A_X(\omega_k) + B_Y(\omega_k)\,B_X(\omega_k))}{T} \\ &+ \frac{i\,(A_Y(\omega_k)\,B_X(\omega_k) - B_Y(\omega_k)\,A_X(\omega_k))}{T} \end{aligned} \tag{A4}$$

The spectral density estimates are estimated from the periodograms at frequency ω by smoothing them with a weighting function spanning several frequencies, j, centered on frequency α_j.

$$S_{XX}(\alpha_j) = \sum_k W_{jk}\, I_{XX}(\omega_k) \tag{A5}$$

The sum of the weights is unity. A variety of weighting functions have been proposed. For this paper we employed the BMDP procedure 1T, which uses a cosine shaped weighting function as the default. In the calculation of the weights a bandwidth parameter β is used which sets the number of periodograms used for each estimate of the spectrum.

$$W_{jk} = \frac{W\left(\frac{a_j - \omega_k}{\beta}\right)}{\sum_l W\left(\frac{a_j - \omega_l}{\beta}\right)} \tag{A6}$$

The spectrum of Y and the cross spectrum for X, Y are estimated similarly.

The coherence (called squared coherence by others) for frequency α is defined by

$$\Re(\alpha) = \frac{|S_{XY}(\alpha)|^2}{(S_{XX}(\alpha)\,S_{YY}(\alpha))} \tag{A7}$$

and the phase by

$$\Phi(\alpha) = \frac{arg(S_{XY}(\alpha))}{2\pi} \tag{A8}$$

In cross-spectral applications, a regression coefficient, b, in the frequency domain is calculated, relating the independent variable X to the dependent variable Y, and that is used to calculate the gain $G_{XY}(\alpha)$:

$$G_{XY}(\alpha) = b_{XY}(\alpha) = \frac{S_{XY}(\alpha)}{S_{XX}(\alpha)} \tag{A9}$$

TABLE 1: SUMMARY STATISTICS FOR THREE MINUTE INTERVALS

	Mean of the Volatilities						
	July 86	Nov 86	Apr 87	Oct 87	Nov 87	Dec 87	Jan 88
S&P 500	.00452	.00353	.00919	.17500	.01600	.00957	.01360
MMI	.00258	.00209	.00851	.18950	.01500	.00954	.01300
NYFE	.00416	.00328	.00867	.20060	.01400	.00811	.01260

	Standard Deviation of the Volatilities						
	July 86	Nov 86	Apr 87	Oct 87	Nov 87	Dec 87	Jan 88
S&P 500	.0053	.0048	.0120	.7100	.0320	.0140	.0250
MMI	.0046	.0043	.0200	1.0500	.0550	.0180	.0420
NYFE	.0060	.0055	.0150	.9700	.0310	.0150	.0390

	Maximum Value of the Volatilities						
	July 86	Nov 86	Apr 87	Oct 87	Nov 87	Dec 87	Jan 88
S&P 500	.065	.052	.246	17.90	.583	.217	.747
MMI	.077	.057	.449	37.50	1.812	.242	1.609
NYFE	.101	.071	.328	29.09	.565	.476	1.519

	Mean Number of Ticks						
	July 86	Nov 86	Apr 87	Oct 87	Nov 87	Dec 87	Jan 88
S&P 500	17.28	15.14	24.61	19.85	20.07	17.99	22.70
MMI	7.94	5.94	14.53	13.71	5.73	6.09	8.31
NYFE	8.42	7.55	13.90	11.44	9.25	8.64	11.32

TABLE 2: VOLATILITY PEAK COHERENCES

		SP vs. MMI		SP vs. NY		MMI vs. NY	
		All Periods	< 20 Minutes	All Periods	< 20 Minutes	All Periods	< 20 Minutes
July 86	Period of Peak Coherence (min.)	17.1	17.1	27.8	18.0	34.5	16.5
	Peak Coherence	.628	.628	.630	.578	.476	.429
	F-value	19.15	19.15	19.35	14.75	8.61	6.67
Nov 86	Period of Peak Coherence (min.)	73.5	11.4	110.2	12.6	79.2	9.6
	Peak Coherence	.753	.708	.843	.772	.664	.581
	F-value	38.50	29.55	72.21	43.37	23.18	14.98
Apr 87	Period of Peak Coherence (min.)	32.7	20	45	20	20	20
	Peak Coherence	.647	.624	.821	.791	.703	.703
	F-value	21.17	18.75	60.80	49.14	28.73	28.73
Oct 87	Period of Peak Coherence (min.)	42.6	7.8	7.8	7.8	7.8	7.8
	Peak Coherence	.868	.808	.752	.752	.751	.751
	F-value	89.83	55.29	38.26	38.26	38.03	38.03
Nov 87	Period of Peak Coherence (min.)	19.7	19.7	51.3	19.0	32.1	19.7
	Peak Coherence	.604	.604	.446	.414	.645	.461
	F-value	16.89	16.89	7.30	6.08	20.94	7.93
Dec 87	Period of Peak Coherence (min.)	64	6.0	9.3	9.3	96	8.7
	Peak Coherence	.657	.588	.715	.715	.431	.275
	F-value	22.33	15.51	30.75	30.75	6.71	2.41*
Jan 88	Period of Peak Coherence (min.)	9.6	9.6	62.1	9.0	18.6	18.6
	Peak Coherence	.620	.620	.856	.792	.816	.816
	F-value	18.36	18.36	80.60	49.48	58.59	58.59

Null Hypothesis: Absolute value of peak volatility coherence is equal to zero.
Alternative Hypothesis: Absolute value of peak coherence is greater than zero.
$F(2,4m)$: $F(2,\infty)$ for (.005) = 5.79
If $F_{table} > F(2,4m)$, then reject null hypothesis; $m = 14.7$; $4m = 58.8$
* Accepts null hypothesis H_0 = absolute value of coherence is zero at the .005 significance level. All unstarred values reject null hypothesis.

TABLE 3: VOLATILITY PHASES, LEADS AND GAINS

		SP vs. MMI		SP vs. NY		MMI vs. NY	
		All Periods	< 20 Minutes	All Periods	< 20 Minutes	All Periods	< 20 Minutes
July 86	Phase at Peak Coherence	-.128	-.128	-.302	-.197	.000*	-.225
	Lead (min.)		-.35		-.56		-.59
	Gain	.872	.872	.739	.684	.752	.473
Nov 86	Phase at Peak Coherence	.006*	.121	-.187	.171	-.376	-.504
	Lead (min.)		.22		.34		-.77
	Gain	.721	.828	.996	1.067	.985	.914
Apr 87	Phase at Peak Coherence	-.625	.087*	-.290	-.236	-.249	-.249
	Lead (min.)		.28*		-.75		-.79
	Gain	.857	1.169	1.238	1.298	.820	.820
Oct 87	Phase at Peak Coherence	-.487	.250	.562	.562	.152	.152
	Lead (min.)		.31		.70		.19
	Gain	1.987	1.163	17.596	17.596	15.699	15.699
Nov 87	Phase at Peak Coherence	-.340	-.340	.070*	.438	-.125*	.040*
	Lead (min.)		-1.07		-.56		.13*
	Gain	1.244	1.244	.509	.456	.501	.285
Dec 87	Phase at Peak Coherence	.094*	.000*	.074	.074	-.423*	CNS
	Lead (min.)		.00*		.11		CNS
	Gain	1.027	1.481	.950	.950	.618	-.361
Jan 88	Phase at Peak Coherence	-.081*	-.081*	-.142	-.208	-.024*	-.024*
	Lead (min.)		-.12*		-.30		-.07*
	Gain	2.715	2.715	1.220	.995	.471	.471

Based on all periods of the cross-spectral analysis for the "All Period" columns and 20 minutes or less for the "20 Minute" column.

A positive phase/lead means the "1st series" leads, while a negative phase/lead means the "2nd series leads" (or equivalently, the 1st series lags). The "1st series" is the contract on the top line of the table heading.
CNS = coherence is not significant (therefore the phase and lead are not important values).
Blanks are placed for the lead for the "All Periods" column since the longer period cycles tend to become synchronized and therefore the lead becomes meaningless.
* The phase, and therefore the lead, is <u>not</u> significant at the .005 level.