INTRADAY MARKET BEHAVIOR AND THE EXTENT OF FEEDBACK BETWEEN S&P 500 FUTURES PRICES AND THE S&P 500 INDEX

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Abstract

In this study we empirically examine the intraday lead/lag relation between S&P 500 futures prices and the S&P 500 index, and whether daily market characteristics are associated with changes in the relation. We estimate daily Geweke measures of feedback and regress time series of these measures on daily price volatility and volume characteristics. Results indicate that the contemporaneous price relation is substantive and that measures of contemporaneous feedback are positively associated with the daily range of the futures price. The primary implication is that the relation between cash and futures prices becomes stronger as futures price volatility increases. As volatility increases, information is being impounded at a faster rate so that futures and equity markets operate more closely as one market. Large futures price moves, by themselves, are not responsible for breakdowns in the stock-futures price relation.

I. Introduction

Theory and empirical evidence suggest that the S&P 500 stock index and its associated futures contract price are closely related throughout a typical trading day by speculative and index arbitrage activity. However, no existing research investigates how changing market characteristics, such as volume, volatility, and program trading, affect the nature and extent of this intermarket price relation on different days.

Following the stock market crash of October 1987, the Brady Commission (1988) examined market behavior around that event to identify contributing factors and make policy recommendations. The Brady Commission found: (i) under normal circumstances a strong intraday relation exists between stock index futures prices and cash prices on the underlying stocks, so that the cash and futures markets essentially operate as one market; (ii) the stock market crash was associated with a breakdown in this normal intermarket price relation; and (iii) it may be appropriate to impose circuit breakers, such as price

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limits and trading halts, to help maintain the normal intermarket price relation. The third finding is especially important because it proposes regulatory interference with the market that may entail potential costs, as well as benefits.

In this research we investigate whether the nature and extent of the relation between S&P 500 futures and index prices vary systematically with changing market conditions on different days. We employ Geweke (1982) measures of feedback to estimate the nature and strength of this intraday price relation on a daily basis. We then use regression analysis to examine whether daily volume and price volatility variables are systematically associated with variation in the nature and strength of this intermarket price relation. This study extends earlier research, such as Kleidon and Whaley (1991), by directly testing whether the strength of the stock-futures price relation varies with market conditions that are often associated with market stress.

The most striking result is that when futures prices vary over a wider range, the magnitude of contemporaneous feedback increases, indicating a strengthening of the dynamic relation between the futures and cash markets. If futures prices vary more widely, more information is processed more quickly in both markets and the futures and equity markets operate more closely as one market. Circuit breakers imposed in the form of price limits may disrupt the orderly interaction between futures and equity markets at the same time market forces may be acting to strengthen the price relation.

II. Motivation and Methodology

We first examine the nature of the relation between S&P 500 futures prices and the S&P 500 index, and determine why this relation might vary in strength or intensity. We discuss three market participants who influence the intermarket price relation during a typical trading day: speculators, hedgers, and arbitragers. Next, we explain how Geweke (1982) measures of feedback are estimated and discuss how they characterize the strength of the price relation. We then describe how changes in price volatility and volume are associated with the expectations of speculators and hedgers and with the cost-of-carry trading of arbitragers. Such changes in price volatility and volume reflect market characteristics that should theoretically influence the strength of the intermarket price relation. This motivates the regression model, which examines how changing market conditions affect the strength of the price relation.

The Role of Speculators, Hedgers, and Arbitragers

As new information arrives during a typical trading day, speculators bid values up or down in both equity and index futures markets. New information should affect the stock index and futures price similarly because both represent a claim against the same assets. Hence, S&P 500 futures prices (F_l) and the S&P 500 index (I_l) should move together over time. Hedgers also operate in both markets, changing the composition of their portfolios over time as they process new information. Portfolio insurers, for example, systematically trade

futures when the underlying index changes by a predetermined amount. The effect of such speculative and hedging activity is that both cash equity and futures prices should move together throughout a typical trading day.

Still, F_t likely adjusts to new information more quickly than I_t . While F_t reflects traders' consensus perception of likely market moves, I_t reflects the average price of the 500 individual stocks that do not all trade every minute. There is inertia in index movements, since individual stocks must all trade at their new prices before I_t can adjust completely to new information. The literature documents a normal intraday price relation in which F_t and I_t move largely in unison each minute. However, I_t also follows movements in F_t for up to forty-five minutes, while F_t follows I_t by no more than one minute (Harris (1989), Herbst, McCormick, and West (1987), Kawaller, Koch, and Koch (1987)).

The strength of this normal intermarket price relation should vary from day to day when market conditions change. As new information affects market sentiment, speculators and hedgers may respond at differing degrees as the markets experience different trading volume, speed of price adjustment, extent of price movement, and so forth. In this environment futures and cash prices may temporarily diverge. At such times the strength of the intermarket price relation is further influenced by arbitrage activity and the cost-of-carry relation.

The cost-of-carry model establishes a trading range for $[F_t - I_t]$, labeled the basis, in terms of arbitrage behavior. The upper bound is determined as some minimum acceptable rate of return plus the cost of carry. This derives from traders' being able to lock in a return by borrowing and buying the S&P 500 stocks while simultaneously selling S&P 500 futures. The cost of carry represents net transactions costs and equals the sum of financing and direct transactions costs less dividends received on the stocks. The lower bound equals some threshold borrowing rate less the cost of carry established from selling stocks and buying S&P 500 futures. Here, the cost of carry equals net financing costs plus dividends owed on the borrowed stocks. We characterize the normal noarbitrage price relation at time t as:

$$\Gamma L, t < [F, -I] < \Gamma U, t \tag{1}$$

where $\Gamma L, t$ and $\Gamma U, t$ represent the lower and upper bounds, respectively.

As long as the basis varies within these bounds arbitrage activity does not occur, so that F_t and I_t are related only through speculative and hedging activity. Suppose, however, that the basis exceeds the upper bound. The expected return to traders from buying stocks and selling futures exceeds the threshold return so that this arbitrage is effected. Futures and index prices subsequently move closer together until the basis again falls within the no-arbitrage bounds. A similar arbitrage occurs when the basis falls below the lower bound as traders sell stocks and buy futures until (1) holds. The basis typically falls outside the bounds only for brief intervals because arbitragers react quickly to the profit

¹This is due to nonsynchronous trading of index stocks, bid-ask spread bounce, and higher transactions costs for index stocks.

opportunity. When this occurs, arbitrage activity increases trading volume in both stocks and futures contracts, and the price relation should strengthen.

Geweke Feedback Measures and the Strength of the Price Relation

When evaluating the strength of the intraday price relation, the contemporaneous relation between F_i and I_i must be considered, as well as minute-to-minute leads and lags. An empirical "strengthening" of the daily intermarket price relation is viewed as contemporaneous and lagged coefficients that are larger in magnitude and/or more highly significant. When the contemporaneous price relation is stronger, more information is being processed and impounded at a faster rate in both futures and index prices so that futures and equity markets operate more closely as one market.

Using intraday transactions data, we measure the strength of the contemporaneous and lagged relations by estimating daily Geweke (1982) feedback measures. These measures characterize the extent of: (i) the contemporaneous minute-to-minute relation between the index and futures prices, (ii) feedback from the futures to subsequent index movements, and (iii) feedback from the index to subsequent futures price movements. These three daily measures can also be combined addictively to measure the extent of total feedback between spot and futures prices for a given day. The choice of daily time intervals corresponds to the availability of volume data used in the regression analysis.

Let I_t equal the last index price and F_t equal the last futures transactions price quoted within each minute. Then i_t and f_t represent the minute-to-minute differences, $(I_t - I_{t-1})$ and $(F_t - F_{t-1})$. Throughout each day, both S&P 500 futures and index price movements may convey predictive information about subsequent price changes in their own market and in the other market. Thus, the intertemporal price relations can be expressed as equations (2) and (3) below:

$$i_t = z_1 + \sum_{k=1}^{M_1} a_k i_{t-k} + \sum_{k=1}^{M_2} b_k f_{t-k} + \varepsilon_{1t}$$
 (2)

$$f_{t} = z_{2} + \sum_{k=1}^{M_{2}} c_{k} i_{t-k} + \sum_{k=1}^{M_{1}} d_{k} f_{t-k} + \varepsilon_{2t}$$
 (3)

or

$$\begin{bmatrix} i_t \\ f_t \end{bmatrix} = \begin{bmatrix} A(L) & B(L) \\ C(L) & D(L) \end{bmatrix} \begin{bmatrix} i_t \\ f_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$
(4)

²The use of first differences assumes that all relevant information is contained in price changes. This assumption is supported theoretically by efficient markets propositions and empirically by time-series tests, which demonstrate that the time series of minute-to-minute prices have unit roots and that first differences are stationary. These tests are available upon request.

with

$$\operatorname{Cov}\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} = \begin{bmatrix} \sigma_{\varepsilon 1}^2 & \sigma_{12} \\ \sigma_{12} & \sigma_{\varepsilon 2}^2 \end{bmatrix} = Y$$

where the distributed lags in (2) and (3) are represented by polynomials (A(L), B(L), C(L), A(L)) in the lag operator $L(L_{it}^k = i_{t-k})$, and each disturbance, ϵ_{it} , is assumed to be independent and identically distributed $N(0, \sigma_{\epsilon i}^2)$. While no autocorrelation is assumed for each disturbance, contemporaneous correlation between disturbances is allowed in Y.

The above model leads us to specify and test four hypotheses reflecting causal priority for a given day's sample. The first reflects the possibility of contemporaneous minute-to-minute correlation between i_t and f_t .

 H_1 : There is no contemporaneous relation between f_t and i_t .

Next, absence of Granger causality implies specific constraints on the distributed lag coefficients in (4) given in the following two hypotheses, where the symbol "—" denotes Granger (1969) causality:

$$H_2$$
: $f_t
ightharpoonup i_t$ $(B(L) = 0)$
 H_3 : $f_t
ightharpoonup i_t$ $(C(L) = 0)$

Finally, to test the hypothesis of no relation between i_t and f_t , we examine the joint hypothesis,

$$H_4$$
: H_1 , H_2 , and H_3 .

Under H_4 , the system in (4) becomes

$$i_t = z'_1 + \sum_{k=1}^{M_1} a'_k i_{t-k} + u_{1t}, \quad \text{Var}(u_{1t}) = \sigma_{u1}^2$$
 (5)

$$f_t = z_2' + \sum_{k=1}^{M_1} d_k' f_{t-k} + u_{2t}, \quad Var(u_{2t}) = \sigma_{u2}^2$$
 (6)

The model in (4) can be estimated as a system of seemingly unrelated regressions with the standard Zellner-Aitken technique, and equations (5) and (6) can be estimated with ordinary least squares. H_1 through H_4 can then be investigated using the estimates of the residual variances and covariances, \hat{Y} , $\hat{\sigma}_{u1}^2$, and $\hat{\sigma}_{u2}^2$ to compute the feedback measures:

$$\hat{F}_{i,\ell} = \ln(\hat{\sigma}_{v1}^2 \cdot \hat{\sigma}_{v2}^2 / |\hat{Y}|) \, \dot{a} \, (n^{-1}) \, \chi_1^2 \, \text{under } H_1$$
 (7)

$$\hat{F}_{f \to i} = \ln(\hat{\sigma}_{u1}^2 / \hat{\sigma}_{\epsilon 1}^2) \, \underline{\mathring{a}} \, (n^{-1}) \, \chi_{M_2}^2 \, \text{under } H_2$$
 (8)

$$\hat{F}_{i\to f} = \ln(\hat{\sigma}_{u2}^2/\hat{\sigma}_{\epsilon 2}^2) \, \mathring{\underline{a}} \, (n^{-1}) \, \chi_{M_2}^2 \, \text{under } H_3$$
 (9)

$$\hat{F}_{i,f} = \hat{F}_{i,f} + \hat{F}_{f \to i} + \hat{F}_{i \to f} \stackrel{a}{\sim} (n^{-1}) \chi^{2}_{(2M_{2}+1)} \text{ under } H_{4}$$
 (10)

where n is sample size, $|\hat{Y}|$ represents the determinant of \hat{Y} , and each measure has an approximate asymptotic chi-square distribution.

Note that the Geweke measures of feedback are simply the log likelihood ratio statistics for the null hypotheses under consideration. This approach provides an advantage over other means for testing H_1 through H_4 , such as the Wald F-test, because the distribution of each Geweke feedback measure is known under the alternative hypothesis (to H_1 through H_4) that feedback is present. The asymptotic distribution of each feedback measure under its alternative hypothesis (to H_1 through H_4) is approximately noncentral chi-square as follows:

$$(n)\hat{F}_{i,f} \stackrel{a}{\approx} \chi'^2 \left(1;(n)F_{i,f}\right) \tag{11}$$

$$(n)\hat{F}_{f\rightarrow i} \stackrel{a}{\simeq} \chi'^{2} \left(M_{2}; (n)F_{f\rightarrow i} \right) \tag{12}$$

$$(n)\hat{F}_{i\rightarrow f} \stackrel{a}{\sim} \chi'^{2} \left(M_{2}; (n)F_{i\rightarrow f} \right)$$
 (13)

$$(n)\hat{F}_{i,f} \stackrel{a}{\sim} \chi'^{2} \left(2M_{2} + 1;(n)F_{i,f}\right) \tag{14}$$

Thus, the Geweke statistics represent cardinal measures of the degree of dependence or the extent of feedback present in a given sample (Geweke (1981, 1982), Koch and Ragan (1987)).

As an example, consider the measures of feedback in each direction, \hat{F}_{f-i} and \hat{F}_{i-j} . Intuitively, both measures associate a higher extent of feedback with a larger reduction in the error variances from estimating (2) and (3) compared with estimating (5) and (6). Such a reduction in error variance must be attributed to the distributed lag coefficients $(b_k$ and c_k) included in (2) and (3) but omitted in (5) and (6). Thus, a greater extent of feedback, say from f_i to i_p implies that the distributed lag coefficients (b_k) in (2) are larger in magnitude and/or more highly statistically significant (with smaller standard errors).

Feedback Measures and Market Characteristics

Collections of these four daily feedback measures are generated by applying this approach to minute-to-minute data for every business day during the last three months before a futures contract expires. Because we know the distribution of each feedback measure, we interpret each statistic as a cardinal meas-

ure of the extent of that kind of feedback. We estimate four linear regression models in which each daily feedback measure is regressed on variables representing changing daily market conditions. As long as (1) holds, the estimated feedback measures reflect the market activity of speculators and hedgers determined primarily by the flow of information during normal nonarbitrage trading periods. When (1) is violated, arbitrage trading supplements information-based trading so that market activity accelerates and the feedback measures vary accordingly.

Regression Model

Changes in price volatility and volume represent the basic market conditions that influence expectations of speculators, hedgers, and arbitragers. We employ three measures of price volatility and two measures of volume. Unfortunately, only daily volume data are available on S&P 500 futures and index trades. We choose one trading day as the appropriate interval to construct the time series of feedback measures.

The first volatility measure is the daily range in the S&P futures price (RFP), which captures volatility in futures prices. As this range becomes greater, so does the likelihood that markets experience shocks that provoke new speculative and hedging activity and require adjustment in F_t and I_t . On days when the futures price range is greater, there is a greater chance that the no-arbitrage trading bounds are violated, leading to market activity that should influence the strength of the intermarket price relation. The second volatility measure is the sample variance of $(F_t - I_t)$ computed over a 390-minute trading day (VAR). All trading activity should vary directly with daily basis volatility. Finally, to identify arbitrage opportunities more precisely we employ a count variable that proxies the frequency of stock index arbitrage opportunities during each day (ARB). This measure compares actual futures price quotes during the day with a minute-to-minute range for the theoretical no-arbitrage futures price calculated from the cost-of-carry framework implied by equation (1).

Kidder, Peabody & Co. provided a daily theoretical futures price based on an assumed dividend stream and overnight financing at the T-bill rate. With this information we compute a theoretical futures price on a minute-to-minute basis, assuming that the theoretical futures-to-index differential is a constant percentage of the index, which varies each minute. To obtain a no-arbitrage trading range, we add/subtract estimated transactions costs and a target return to/from the computed theoretical futures price. Arbitrage opportunities are then presumed to occur when the futures price breaks out of this range and thus covers transactions costs and yields the assumed target return. Our measure of arbitrage frequency is the number of futures price quotes that fall outside of this no-arbitrage trading range during a day.

The two volume measures are the daily number of advancing issues (ADV) and declining issues (DEC), respectively, on the New York Stock Exchange (NYSE). Separating volume this way allows us to capture the effect of runs where market sentiment systematically drives the futures price higher or lower.

When we replace these measures with advancing and declining volume the results are virtually identical.

The full regression model is:

$$W_i = \gamma_0 + \gamma_1 T + \gamma_2 D + \gamma_3 ADV + \gamma_4 DEC + \gamma_5 RFP + \gamma_6 VAR + \gamma_7 ARB + \mu$$
 (15)

where

 W_i = each of the four feedback measures, i = 1, 2, 3, 4;

T = time trend;

D = vector of dummy variables for the day of the week: D1 = 1 for Monday, 0 otherwise; D2 = 1 for Tuesday, 0 otherwise; D3 = 1 for Wednesday, 0 otherwise; D4 = 1 for Thursday, 0 otherwise; Friday is the omitted group;

ADV = the daily number of advancing stock issues on the NYSE;

DEC = the daily number of declining stock issues on the NYSE;

RFP = the daily range of the futures price (F_i) ;

VAR = the daily variance of the futures to cash basis $(F_t - I_t)$; and

ARB = the daily frequency of futures transactions when arbitrage is justified.

The time-trend and day-of-the-week dummy variables indicate whether there are systematic timing patterns behind daily movements in the extent of feedback.³

III. Empirical Results

Data

Minute-to-minute data on prices of the nearby S&P 500 futures contract and the S&P 500 index are obtained from the Chicago Mercantile Exchange for

$$(X-(r-1)/3)^{1/2} \stackrel{a}{\underline{a}} N[\lambda + (2r+1)^{1/2}, 1]$$

We employ this transformation in the regression models as follows:

$$\begin{array}{ll} W_{i,f} &= ((n)\hat{F}_{i,f} - (0/3))^{1/2} \\ W_{f-i} &= ((n)\hat{F}_{f-i} - (44/3))^{1/2} \\ W_{i-f} &= ((n)\hat{F}_{i-f} - (44/3))^{1/2} \\ W_{i,f} &= ((n)\hat{F}_{i,f} - (90/3))^{1/2} \end{array}$$

Regression models explaining these transformations of the feedback measures contain error terms that have approximate normal distributions, and using ordinary least squares estimation is asymptotically justified. Regressions have also been fitted to the actual feedback measures with robust results.

³Any noncentral chi-square statistic can be manipulated with a nonlinear, monotonic transformation so that its approximate distribution is normal. Geweke (1982) suggests the following: If $X \stackrel{a}{=} \chi'^2(r;\lambda)$ where r= the degrees of freedom and $\lambda=$ the noncentrality parameter, then

the fourth quarters of 1984, 1985, and 1986. Because the index is generally reported only once each minute, we match the last futures transactions price reported each minute with that minute's index value. During 1985 the stock market was open from 8:30 a.m. to 3:00 p.m. CST, while the futures market remained open fifteen minutes later. We ignore all futures prices reported after the last index quote. This provides 390 pairs of observations over each six-and-one-half-hour trading day. To estimate system (4), we must select finite lag lengths, M_1 and M_2 . Geweke (1978) suggests that long lags on the dependent variable minimize the chance of serially correlated errors, while shorter lags on other variables retain power in the hypothesis tests. In the following tests M_1 equals sixty minutes for the lagged dependent variables and M_2 equals forty-five minutes for the independent variables in system (4).

Time-Series Characteristics of the Feedback Measures

We compute feedback measures for all trading days of the nearby December futures contract in each year investigated. Because they are similar for all years, we discuss only the results for the fourth quarter of 1986. The specific Geweke feedback measures and marginal significance levels associated with the tests of H_1 through H_4 are available on request.

The measures indicate that there is always substantive contemporaneous feedback between i_i and f_i , and that Granger causality often runs in both directions. Specifically, the contemporaneous feedback measures reject H_1 (no contemporaneous relation) on every day examined. This represents powerful and robust evidence that the two prices move largely in unison on a minute-tominute basis throughout each trading day. The magnitude and significance of the Geweke measures, in fact, indicate that the contemporaneous relation dominates any lead or lag relation on all days. $H_2(f_t + i_t)$ is rejected on all but three days at the .05 significance level, while H_3 $(i_t
ightharpoonup f_t)$ is rejected on all but twenty-four days. Finally, total feedback rejects the joint hypothesis of no relation (H_4) on every day examined because, although H_2 and/or H_3 are not rejected on some days, H_1 is rejected on all days. Cumulatively, the results indicate that contemporaneous feedback not only occurs more frequently than the other types, but that it is also generally "stronger." These estimates support the notion that the markets for stock index futures and equities act as one market.

To determine whether there is any discernible trend in feedback intensity, we plot $n\hat{F}_{f\rightarrow i}$ and $n\hat{F}_{i\rightarrow f}$ for each day in the fourth quarter of 1986 in Figures I and II, respectively. The asymptotic distribution of each feedback measure is approximately χ_{45}^2 under H_2 ($f_t
ightharpoonup in Mark 1000). The critical value of a <math>\chi_{45}^2$ variable at the .05 significance level (61.65) is referenced in the figures by a solid line. On days in which the feedback measures lie above this line, H_2 or H_3

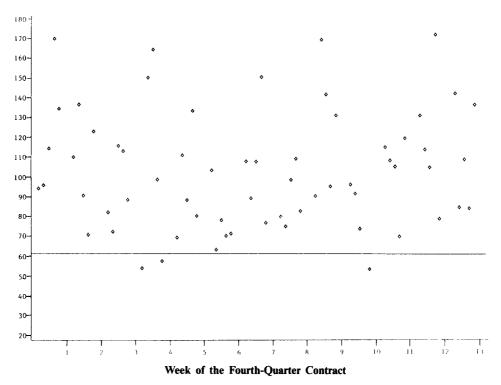


Figure I. Daily Measures of Feedback from f_i to i_t , $(n)F_{f+i}$ Fourth Quarter, 1986.

is rejected with more than 95 percent confidence. Note that time to expiration has little apparent effect on the extent of feedback in either direction.

Regression Results

Table 1 presents the parameter estimates and summary statistics for the four regression models using daily data for the last three months of 1986. The Durbin-Watson statistics indicate there is no significant autocorrelation in any model's residuals. The adjusted R^2 measures range from .132 to .507. Given the nature of the dependent variables, it is not surprising that substantial variation exists in each feedback measure that is not attributable to these market characteristics. Finally, for all of the models, except that explaining $W_{i\rightarrow f}$, the F-statistics reject the null hypotheses that no daily market characteristics affect movements in the feedback measures.

Estimates of the model parameters reflect the effects of individual market characteristics on the feedback measures. In all cases, time-trend and day-of-the-week effects are negligible. This suggests that the extent of the intermarket price relation does not systematically increase or decrease as expiration approaches, and that there are no systematic weekly patterns in the extent of

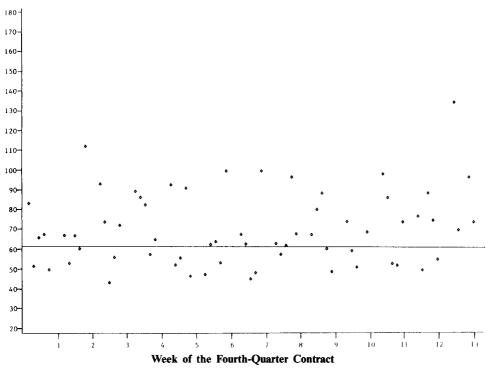


Figure II. Daily Measures of Feedback from i, to f, $(n)\hat{F}_{i-f}$ Fourth Quarter, 1986.

feedback.⁴ The effect of the other market factors is presented for each feedback measure.

Consider first the regression model explaining contemporaneous feedback. The daily range of futures prices is the only market characteristic that displays a significant positive association with $W_{i,f}$. Days in which futures prices vary more widely are systematically associated with days displaying stronger contemporaneous feedback. On such days more information is presumably being processed more rapidly in both markets, so that futures and equity markets operate more closely as one market. This result suggests that the normal intermarket price relation is enhanced, not weakened, when futures prices vary more widely.

Price volatility appears to be marginally important, reinforcing the inter-

⁴We also test three extensions of model (15) incorporating an expiration day dummy variable, an expiration week dummy variable, and both dummy variables combined. The coefficient estimate for the expiration day dummy is almost always positive, although its marginal significance level varies widely across feedback measures. The expiration week dummy is also positive, indicating that average feedback is stronger that week than during the previous twelve weeks of 1986. Finally, feedback on expiration day is still higher than on the other four days in the last week of trading. Thus, feedback generally increases near expiration of the futures contract when index arbitrage unwinding is known to occur. The remaining parameter estimates are generally robust across these extensions.

TABLE 1. Regression Estimates for the Transformed Feedback Measures: Daily Data, Fourth Quarter, 1986.

Independent Variables	Dependent Variables ^a			
	$W_{i,f}$	$W_{f \rightarrow i}$	$W_{i op f}$	$W_{i,f}$
T = time trend	0.001 (0.1) ^b	-0.007 (-0.5)	0.025 (1.8)	0.007 (0.5)
D1 = Monday dummy	0.404 (1.1)	-0.013 (-0.0)	0.721 (1.6)	0.578 (1.1)
D2 = Tuesday dummy	0.148 (0.4)	0.596 (1.3)	-0.216 (-0.5)	0.302 (0.5)
D3 = Wednesday dummy	0.281 (0.7)	0.739 (1.6)	-0.306 (-0.6)	0.439 (0.8)
D4 = Thursday dummy	0.421 (1.1)	0.427 (0.9)	-0.062 (-0.1)	0.501 (0.9)
ADV = number of advancing issues on the NYSE	$0.188xE^{-2} $ (0.7)	$0.595xE^{-2} $ (1.9)	$-0.279xE^{-2}$ (0.9)	$0.304xE^{-2}$ (0.8)
DEC = number of declining issues on the NYSE	$0.227xE^{-2} $ (0.8)	$0.706xE^{-2} $ (2.1)	-0.360xE ⁻² (-1.0)	$0.360 xE^{-2}$ (0.9)
RFP = range of futures price movements	$0.416xE^{-2} $ (3.1)	$0.782xE^{-2} $ (4.7)	0.116xE ⁻² (0.7)	$0.773xE^{-2}$ (3.8)
VAR = variance in the basis	$0.387xE^{-3} $ (1.6)	$-0.771xE^{-4}$ (-0.3)	$0.421xE^{-3}$ (1.4)	$0.409xE^{-3}$ (1.1)
ARB = arbitrage frequency	-0.317xE ⁻³ (-1.1)	-0.368xE ⁻³ (-1.0)	$0.130xE^{-3} $ (0.3)	-0.377xE ⁻³ (-0.8)
Constant	8.463 (2.2)	-3.353 (-0.7)	10.662 (2.2)	9.511 (1.6)
Adjusted R ²	0.437	0.507	0.132	0.471
F-ratio (marginal significance level)	5.9(.0001)	7.5(.0001)	2.0(.0570)	6.6(.0001)
Durbin-Watson statistic	1.765	1.743	2.181	1.756
First-order autocorrelation	0.088	0.090	-0.091	0.094
Number of observations	64	64	64	64

^aDependent variables are transformed Geweke feedback measures for contemporaneous feedback $(W_{i,f})$, feedback from futures to the index (W_{f-i}) , feedback from the index to futures (W_{i-f}) , and total feedback $(W_{i,f})$.

^bt-statistics are in parentheses.

pretation above. However, market volume and the frequency count variable of arbitrage opportunities display no notable relation to contemporaneous feedback. We also estimate a model in which we replace ARB with a dummy variable assigned a value of one on days where thirty or more futures quotes fall outside the no-arbitrage trading range described above, and zero otherwise. The coefficient estimates for this dummy are similar to those for ARB in Table 1, and the other results are also robust. The daily range of futures prices may serve as a better proxy for arbitrage, as well as a sentiment indicator of speculator activity. As prices vary more, the likelihood becomes greater that traders will take speculative and arbitrage positions. No market characteristics are systematically associated with a decrease in feedback or a breakdown in the normal contemporaneous price relation.

Next, consider the second regression explaining feedback from futures to the index. The range of futures prices again appears to be a significant determinant of W_{f-i} , but in this regression it is joined by advancing and declining volume. On days with wider futures price movements, feedback from futures prices to the index is generally stronger. On such days the distributed lag coefficients that embody the lead from futures prices to the index are apparently systematically larger in magnitude and/or more highly significant. The same holds for advancing and declining volume, which displays a positive relation to W_{f-i} . During the fourth quarter of 1986 the NYSE recorded several of the busiest trading days in history, measured by total volume. Again, no factors are associated with a breakdown in feedback from futures to the index.

The third regression model reflects the relation between daily market characteristics and feedback from the index to futures prices, $W_{i op f}$. The observation that no parameter estimates are statistically significant (at the .10 level), combined with the relatively poor fit and insignificant F-test, indicates that noise accounts for virtually all of the day-to-day variation in $W_{i op f}$. This is not surprising given the earlier results that reveal a frequent lack of significance and robustness for this feedback measure.

Finally, the fourth regression model on the composite measure of total feedback, $W_{i,f}$, behaves much like the first regression on contemporaneous feedback. This is presumably because contemporaneous feedback dominates the other two measures of feedback in the composite measure. Hence, the interpretation of the last regression follows that for $W_{i,f}$.

These regression results make intuitive sense in light of the increased stress under which traders operate when prices become increasingly volatile. Larger price moves create a stronger incentive to monitor the markets closely and act

⁵We experimented with alternative measures of price volatility and volume, including (i) daily volume for nearby S&P 500 futures contracts, (ii) daily volume for all S&P 500 futures contracts, (iii) daily volume on the NYSE, and (iv) the number of daily block trades of more than 10,000 shares on the NYSE. The most important result is that the coefficients of the statistically important variables remain robust across tests. Unfortunately, meaningful data for measures reflecting bid-ask spreads and the nonsynchronous trading of stocks are not available.

quickly on any perceived opportunities. As long as trades can be executed efficiently, related markets should move together.⁶

IV. Summary and Conclusions

This research empirically examines the nature of the intraday price relation between S&P 500 futures and the S&P 500 index. We calculate daily Geweke (1982) measures of feedback for each day throughout the life of a nearby futures contract and use these measures to investigate whether daily feedback can be explained in a regression on a time trend, day-of-the-week dummies, and market characteristics such as trading volume, price volatility, and the frequency of index arbitrage opportunities. This procedure enables comparative analysis of the intermarket price-adjustment process, and provides a means for determining how daily market characteristics influence the process.

The feedback measures indicate that the contemporaneous minute-to-minute price relation between futures and the index dominates all lead/lag relations. Granger causality also runs from futures to the index with greater frequency and to a greater extent than from the index to futures. Regression results indicate that the daily range of the futures price exhibits a significant positive relation to contemporaneous feedback, suggesting that on days when futures prices vary over a wider range the intermarket price relation between futures and the index is strengthened. No other factors affect the contemporaneous relation and no factors are associated with a significant reduction in the extent of any kind of feedback. Feedback from futures prices to subsequent index values also displays a significant positive relation to the daily range of futures prices. However, feedback from the index to futures prices reveals day-to-day variation that is virtually all noise.

The primary implication is that the relation between spot and futures prices generally becomes stronger, with shorter lags in adjustment, as price volatility increases. This makes intuitive sense in light of the increased stress under which traders operate when prices become increasingly volatile. The results suggest several policy implications regarding price limits in the futures and equity markets. First, stock index futures and equity markets operate as one market because futures and equity prices move largely in unison on a minute-to-minute basis. This indicates that information is normally processed quickly in both markets. Second, the contemporaneous price relation is strengthened on days when futures prices vary over a wider range. Thus, larger futures price moves, by themselves, may not be the primary cause of a breakdown in the stock-futures price relation.

⁶Our sample period does not include any events of the magnitude associated with the stock market crashes of October 1987 and October 1989. Several recent studies (Dwyer and Hafer (1988), Roll (1988)) investigate market relations around the October 1987 crash. Gaps in market activity and limited data availability prevent us from applying our analysis to data for these periods.

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