Trades, Basis, and Price Revisions in the S&P Depositary Receipts

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Standard and Poor's Depositary Receipts (SPDRs) are traded like a stock to track the performance of S&P 500 index, and there exists contemporaneous trading of S&P 500 index futures to track the same index portfolio. The basis reveals the instantaneous price difference of the S&P 500 index portfolio observed in index futures and SPDRs. This study finds that the basis conveys more information than trades for the intra-day quote price revisions in the SPDRs, and our findings are consistent with a price revision process that the basis transmits innovative information from futures prices and induces permanent price changes in the SPDRs.

Keywords: trades, basis, S&P Depositary Receipts, trade informativeness, basis informativeness, Granger causality

INTRODUCTION

Glosten and Milgrom (1985) and Easley and O'Hara (1987) developed the idea that trades are signals of private information causing price revisions in a security market. They suggest that new information is revealed after the trading by some informed traders. These trades, in and of themselves, could permanently impact the security price. Hasbrouck (1991) proposes a measure of trade informativeness in a market with asymmetrically informed participants intended to assess the impact of trade innovations on efficient price processes. The efficient price is the expected end-of-trading security value conditional on all public information n and assumed to evolve as a random walk. Trade informativeness is the ratio of trade-correlated innovation to the variance of changes in the efficient price.

Index-tracking securities have been successful investment innovations in the financial markets. Standard & Poor's index futures traded on the Chicago Mercantile Exchange and Standard & Poor's Depository Receipts (SPDRs) traded on the American Stock Exchange (AMEX) are two pioneering index securities that track the performance of the S&P 500 index portfolio.

Although SPDRs are traded like individual stocks on the AMEX, the contemporaneous trading of S&P 500 index futures distinguishes SPDRs from the other securities traded on the stock exchange. The trading of S&P 500 index futures reveals the certainty equivalent value of the S&P 500 index portfolio on the maturity date. The S&P 500 index futures price thus becomes a reference for setting the price of SPDRs. After adjusting the S&P 500 index futures prices for the cost of carry and the SPDRs price for accumulated dividends, there are differences between the two adjusted price series caused by the different speeds with which new information is processed in the different markets. We define these differences as the S&P 500 index *basis*.

The hypothesis that price revisions in SPDRs are induced by the basis is supported by the finance literature investigating spot-futures interactions. Most studies report that futures prices lead the spot price, and futures prices are dominant in the price discovery process. These studies attribute their findings to high leverage effects, less restrictive regulation, and lower transaction costs in futures markets (Tsay, 2002; Hasbrouck, 2003). Once the basis is revealed, new information is transmitted from the futures market to the SPDRs market.

SPDRs have two distinct characteristics: (1) SPDRs are traded like a stock to track the performance of the S&P 500 index portfolio, and (2) there is contemporaneous trading of S&P 500 index futures to track the same index portfolio. Trades and basis provide competing sources of information for quote price revisions in the SPDRs. The paper aims to compare trade informativeness with basis informativeness in the SPDRs market. Our comparison confirms that the basis conveys more information than trades for the intraday price revisions in the SPDRs.

The empirical results presented should be of interest to traders and policymakers. Traders in the S&P 500 index market can design their trading strategy depending on the basis. One trading strategy based on basis would be index arbitrage, which exploits the difference between spot and futures prices. Active index arbitrage activities improve the quality of S&P 500 index markets and attract large trading volumes of SPDRs.[1] Policymakers would justify the inclusion of corresponding futures contracts when they design instruments to be traded in active index-tracking markets.[2]

INDEX-TRACKING SECURITIES AND SPDRS

Standard & Poor's index futures and SPDRs are two pioneering index securities that track the performance of the S&P 500 index portfolio. The S&P 500 index futures contract began to trade on the Chicago Mercantile Exchange (CME) in April 1982, while SPDRs were introduced by the AMEX on January 29th, 1993.

S&P 500 index futures and SPDRs allow investors to participate in a broad market movement without actually buying or selling large numbers of stocks. As basket securities, one major advantage is that they provide uninformed traders with better trading vehicles because information asymmetry can be reduced in these markets. Subrahmanyam (1991) presents a model to characterize the trading strategy of discretionary uninformed traders. These uninformed traders can choose to execute their portfolio trades either in the market for the basket security or the underlying securities markets. He finds that because of the "diversification" or "information offset" effect of the independent trades of informed traders who possess firm-specific and/or systematic information in the basket security, the total effect of informed trading is less damaging to discretionary uninformed traders in basket security than in its underlying individual securities markets.

Gorton and Pennacchi (1993) also illustrate the existence of basket security can reduce the information advantage of informed traders over uninformed traders and minimize uninformed traders' loss to informed traders. They prove that for any set of individual security portfolio weights that would be chosen by an uninformed trader, if a basket security was constructed with these same portfolio weights, then the uninformed trader would receive a higher expected return and face a lower variance, by holding this basket security rather than the individual securities that make up the portfolio.

Subrahmanyam (1991) and Gorton and Pennacchi (1993) provide the theoretical foundation for innovative index-tracking securities, such as S&P 500 index futures and SPDRs. SPDRs are exchange-traded funds (ETFs) listed and traded on the American Stock Exchange like common stocks. Like all ETFs, SPDRs represent an undivided ownership interest in the portfolio of stocks held by the SPDR Trust, i.e., the common stocks of the S&P 500 index. So, the SPDRs are pooled investments designed to provide investment results that generally correspond to the price and yield performance, before fees and expenses, of the S&P 500 index. Each unit of SPDRs carries a market value of approximately one-tenth the value of the underlying S&P 500 index.

As opposed to actively managed mutual funds, SPDRs is a form of passive investing. The other major difference between SPDRs and open-ended mutual funds includes that SPDRs are continuously priced and traded the whole day on the exchange, while mutual funds have specific trade windows during the day. Compared with regular common stocks, investors can sell them short without being subject to uptick rule. Besides, Poterba and Shoven (2002) explain ETFs' advantage over traditional equity mutual funds due to the special tax technique known as "redemption in kind."

HYPOTHESES

Subrahmanyam (1991) argues that basket securities, such as SPDRs, would attract trades from uninformed traders. Gorton and Pennacchi (1993) demonstrate that basket securities, such as SPDRs are subject to less information asymmetry. Hypothesis I can be stated as: *trades of SPDRs carry little information for price revisions in SPDRs.*

Stock indexes are usually packaged in different ways and traded in different markets. In a perfectly frictionless world, information would be impounded into all markets simultaneously, and price movements in multiple markets would be contemporaneous. In the face of information asymmetry, however, different market structures and security designs provide informed traders incentives to concentrate in one specific market to maximize their profit, which then influences the processing of new information in different markets. If informed traders are more likely to choose to trade in one particular market, prices in this market tend to lead to prices in other markets.

Establishing spot positions in the S&P 500 index would require a huge initial investment and be very expensive and time-consuming because it would involve as many as 500 individual stock transactions. Investors are subject to the uptick rule in this market. The S&P 500 spot index market is not a good choice for informed traders, especially after the introduction of SPDRs.

S&P 500 index futures and SPDRs can be purchased or sold directly in the market, saving investors lots of initial investment, time, and trading costs, and they are exempt from the uptick rule. Compared to SPDRs, S&P 500 futures can be traded on margin, providing investors with higher leveraged returns than SPDRs on the same amount of capital available. Minimum tick sizes are 0.05 index points in the S&P 500 futures market and 1/32 for SPDRs, equivalent to 0.3125 index point.[3] Smaller minimum tick sizes imply a lower minimum bid-ask spread, which induces lower transaction costs in the S&P 500 futures market.

For all these reasons, traders with superior information prefer to trade in the S&P 500 futures market, which would imply that futures markets react more quickly to new information and that index futures prices lead SPDRs prices. This lead-lag relationship between futures and SPDRs prices tends to be weakened by the trading restriction applied to institutional traders. Large institutional traders usually have superior market-wide information, but many are restricted by regulation from trading in futures markets.

Kawaller, Koch, and Koch (1987) investigate intraday price relationships between S&P 500 futures and the index. They find that the lead from futures to cash prices extends from 20 to 45 minutes, while the lead from cash prices to future prices rarely extends beyond one minute. Stoll and Whaley (1990) find that the S&P 500 and the Major Market Index futures returns lead stock index returns by about five minutes on average and also tend to lead even the returns of actively traded component stocks, but there is weak evidence to show that stock index returns lead futures returns. Chan (1992) studies the lead-lag relation between intraday futures and cash index prices, considering the effect of infrequent trading of the index component stocks. He confirms that futures prices are dominant in leading the cash index.

Chu, Hsieh, and Tse (1999) analyze the factors that affect informed traders' choice of the three S&P 500 index markets: the S&P 500 index futures, the S&P 500 spot index, and SPDRs. Their study of price discovery process in the three markets indicates that all three markets are contributing to the price discovery process, although information is impounded in the futures prices faster than in the SPDRs prices and the S&P 500 spot index.

For lower trading costs and the leverage effect, informed traders prefer to trade in the S&P 500 index futures market. The index futures market tends to incorporate new information faster than the SPDRs market. The S&P 500 index basis provides investor index arbitrage opportunities. Index arbitrage then facilitates integration and information transmission across markets, so we hypothesize that the S&P 500 index basis conveys information and provides the direction for price revisions of the SPDRs. Hypothesis II expresses the causality relationship between SPDRs price revision and the S&P 500 index basis and it can be stated as: *the S&P 500 index basis Granger-causes SPDRs price revisions.*

Granger causality measures precedence and information content between two variables. The Granger (1969) approach to whether *x* causes *y* is to see how much of the current *y* can be explained by past values of *y*, and then to see whether adding lagged values of *x* can improve the explanation. *y* is said to be Granger-caused by *x* if lagged values of *x* help in the prediction of *y*, or, equivalently, if the coefficients on the lagged values of *x* are statistically significant. Hypothesis II means that SPDRs' quote revisions can be explained better by including past values of the basis than by using only the lagged values of quote revisions.

Our third hypothesis is about the information content of the S&P 500 index basis. Given the structure of S&P 500 index markets, we presume that the S&P 500 index basis conveys information and has a permanent impact on the SPDRs price. The S&P 500 index futures market impounds new information faster than the market for SPDRs, and S&P 500 futures prices move to new equilibrium prices ahead of SPDRs prices, which incur the S&P 500 index basis. The basis provides the investor index arbitrage opportunities. Index arbitrage then facilitates integration and information transmission across markets, and SPDRs prices subsequently move to new equilibrium prices. Hypothesis IIII can be stated as: *the S&P 500 index basis conveys information and has a permanent impact on the SPDRs prices.*

DATA AND METHOLOGY

Data

The data include intraday transaction data for the S&P 500 index futures and intraday quote and trade data for SPDRs. We chose the sample periods of February, March, and April in 1993, 1995, 1997, and 2000.

The intraday transaction and quotation data of SPDRs are obtained from the TAQ Database. All data series are fully examined, and outliers are excluded. To avoid negative series correlation caused by bid-ask bounces, we use the mid-quote of SPDRs to calculate price revisions. We also use the mid-quote to estimate the S&P 500 index basis.

The intraday transaction data for S&P 500 index futures comes from the Futures Industry Institute Data Center. Each year, four regular S&P 500 index futures contracts expire in March, June, September, and December. The database provides every futures contract trade record with tick symbol, expiration month of the contract, date and time of transaction stamped to the nearest second, and the futures trade price. The futures trading volume and bid and ask quote data are not available. We consider only the most active contract, i.e., the contract with the most trades. Records marked as cancelled, corrected, or inserted are deleted. Those reported out of time sequences are also eliminated.

To make the two series more comparable in reflecting the underlying S&P 500 index portfolio, we adjust the SPDRs mid-quotes and the index futures prices. SPDRs pay quarterly dividends that actually represent a pro-rata amount of regular cash dividends for the stocks held by the SPDR Trust, net of accumulated Trust expenses and fees. We retrieve the dividend information from the CRSP database. Each SPDRs unit carries a market value of approximately one-tenth the value of the underlying S&P 500 index. Our final S&P 500 spot price adjusted from SPDRs prices is calculated by excluding the accrued dividend equivalent from SPDR mid-quotes and then multiplying it by 10.

Based on the perfect tracking portfolio approach, the futures price represents the certainty equivalent value of the index on the maturity date. To derive the current value of the underlying S&P 500 index portfolio, the futures price is adjusted for the cost-of-carry at the risk-free rate. The adjusted futures price is defined as $af_t = f(t,T)/e^{(r-d)(T-t)}$, where $f(t,T)$ is the futures price at time t for a contract that matures at time T; r is a non-stochastic risk-free rate; and d is the expected continuous compounded dividend yield.

We take the 3-month Treasury constant maturity interest rates obtained from FRED® Monthly Interest Rate Dataset as the risk-free rate. The dividend yield for the S&P 500 index portfolio is obtained as follows. First, we collect monthly dividends per share on the S&P 500 index from the Standard & Poor's Quarterly

Dividend Record Issue. Then the dividend yield is computed by dividing the monthly dividends per share on the S&P 500 index by the monthly average of the S&P 500 Daily Stock index.[4]

To calculate the S&P 500 index basis, we match the two adjusted index value series following the MINSPAN technique proposed by Harris et al. (1995). For each trading day, we obtain the record of the last market to have an opening trade or quote price and then take the most recent record of the other market to form the first tuple. We also look forward to checking subsequent records to ensure that the time between prices of two markets in the same tuple is minimized. The next tuple is formed in the same manner.

TABLE 1
DESCRIPTIVE STATISTICS of S&P 500 FUTURES AND APDRS ADJUSTED PRICES

Panel A Descriptive statistics for original data set before matching

Year		Adjusted Price				Number of Observations
		Mean	**Minimum**	**Median**	**Maximum**	
1993	Futures	445.10	428.42	446.56	457.83	179,217
	SPDRs	444.25	425.11	445.75	455.75	9,420
1995	Futures	494.38	468.62	494.96	515.04	172,806
	SPDRs	493.85	468.30	493.66	515.10	14,089
1997	Futures	784.16	733.11	787.51	818.16	271,598
	SPDRs	781.93	732.20	784.85	817.68	39,546
2000	Futures	1,427.87	1,323.95	1,415.66	1,556.92	226,009
	SPDRs	1,434.67	1,324.99	1,425.05	1,556.45	128,520

Panel B Descriptive statistics for matched dataset

Year		Adjusted price after match				Number of Matched pairs	Average Time Span for Matched Pairs (seconds)
		Mean	**Minimum**	**Median**	Maximum		
1993	Futures	444.82	428.42	446.20	457.68	9,047	4.59
	SPDRs	444.25	426.11	445.75	455.75		
1995	Futures	494.05	468.72	494.77	515.04	13,853	4.28
	SPDRs	493.86	468.30	493.66	515.10		
1997	Futures	782.74	733.21	786.18	817.86	36,037	3.33
	SPDRs	782.22	732.52	785.21	817.68		
2000	Futures	1,432.31	1,324.45	1,420.02	1,556.92	85,331	3.26
	SPDRs	1,432.12	1,324.99	1,420.02	1,556.45		

Table 1 reports the basic statistics of S&P 500 futures and SPDRs adjusted prices for the original data set before matching in Panel A and for the matched data set in Panel B. Panel A indicates that many fewer quotations in the market for SPDRs than for S&P 500 futures. The total numbers of SPDRs quotes during the three-month sample periods are all less than 15% of futures trades in 1993, 1995, and 1997. In 2000, the total number of quotes for SPDRs increased significantly, becoming more than 50% of the number of trades for the S&P 500 futures. Panel B reports the average time spans for the matched price pairs. They are quite low: 4.59, 4.28, 3.33, and 3.26 seconds in 1993, 1995, 1997, and 2000, respectively.

Methodology

Two econometric methods are employed to test the three hypotheses in this paper.

Granger Causality

We use the bivariate autoregressions to test for causality relationship between the two variables: SPDRs quote revisions and the S&P 500 index basis:

$$P_t = a_1 P_{t-1} + a_2 P_{t-2} + \cdots + b_1 B_{t-1} + b_2 B_{t-2} + \cdots + \nu_{1,t}$$
$$B_t = c_1 P_{t-1} + c_2 P_{t-2} + \cdots + d_1 B_{t-1} + d_2 B_{t-2} + \cdots + \nu_{2,t} \tag{1}$$

where, $P_t = 100 \times log(\, q_t/q_{t-1})$ and q_t is SPDRs mid-quote price; B_t is S&P 500 index basis and $\nu_{1,t}$and $\nu_{2,t}$ are zero-mean, serially uncorrelated disturbance terms. $B_t = 100 \times log(\, af_t/aq_t)$, where af_t is S&P 500 futures prices adjusted for cost of carry, and aq_t is SPDRs mid-quotes adjusted for accrued dividend equivalent then times 10.

According to Granger (1969), B_t Granger-causes P_t if P_t can be explained better by including past values of B_t than by using only the lagged values of P_t, i.e., the coefficients on the lagged B_t are statistically significantly different from zero. It is worth noting that the statement "B_t Granger-causes P_t" does not imply that P_t is the effect or the result of B_t. Granger causality measures precedence and information content but does not by itself indicate causality in the more common use of the term.

S&P 500 Index Basis Informativeness

Because trading conveys information and has a permanent impact on security prices, Hasbrouck's (1991) uses trade variables to estimate trade informativeness. As an extension of Hasbrouck's (1991) trade informativeness measurement, we estimate basis informativeness to test our hypothesis that the S&P 500 index basis conveys information for price revisions in the SPDRs. Our vector moving average (VMA) models are specified as follows:

$$P_t = a_0^* \nu_{1,t} + a_1^* \nu_{1,t-1} + a_2^* \nu_{1,t-2} + \cdots + b_0^* \nu_{2,t} + b_1^* \nu_{2,t-1} + \cdots$$
$$B_t = c_0^* \nu_{1,t} + c_1^* \nu_{1,t-1} + c_2^* \nu_{1,t-2} + \cdots + d_0^* \nu_{2,t} + d_1^* \nu_{2,t-1} + \cdots \tag{2}$$

where, P_t is quote revision, B_t is S&P 500 index basis and $\nu_{1,t}$and $\nu_{2,t}$ are zero-mean, serially uncorrelated disturbance terms with $Var(\nu_{1,t}) = \sigma_1^2$, $Var(\nu_{2,t}) = \Omega$, and $E(\nu_{1,t}\nu_{2,t}) = 0$. The variance of efficient price innovation σ_w^2 and the absolute (relative) measure of basis informativeness $\sigma_{w,B}^2$ (R_w^2) can be estimated by:

$$\sigma_w^2 = (\textstyle\sum_{t=0}^{\infty} b_i^*)\Omega\big(\textstyle\sum_{t=0}^{\infty} b_i^{*'}\big) + (\textstyle\sum_{t=0}^{\infty} a_i^*)^2 \cdot \sigma_1^2 \tag{3}$$

$$\sigma_{w,\,B}^2 = (\textstyle\sum_{t=0}^{\infty} b_i^*)\Omega\big(\textstyle\sum_{t=0}^{\infty} b_i^{*'}\big) \tag{4}$$

$$R_w^2 = \frac{\sigma_{w,\,B}^2}{\sigma_w^2} \tag{5}$$

In our estimation procedure, VAR is truncated at lag 20 and VMA is truncated at lag 10.[6]

EMPIRICAL RESULTS

Trade Informativeness

We first estimate the trade informativeness for SPDRs and the 90 underlying individual securities. The S&P 500 index comprises 500 stocks chosen for market size, liquidity, and industry group representation. The 90 sample stocks are selected based on the following procedure: First, we excluded the stocks that added or deleted from the S&P 500 index compositions from 1993 to 2000. Then, we rank the remaining stocks based on their average market capitalization and divide them into three groups. In each group, we pick the median 30 stocks. Of these 90 stocks, 87 are traded on the NYSE and three are traded on the NASDAQ. To exclude the effect of different trading mechanism we substitute the NASDAQ listed stocks with NYSE listed stocks of similar size.

TABLE 2
TRADE INFORMATIVESS OF SPDRS AND ITS UNDERLYING STOCKS

Year	Trade informativeness (%)						
	SPDRs	Underlying stocks					
		Mean	Minimum	1st Quartile	Median	3rd Quartile	Maximum
1993	1.57	29.00	0.61	20.26	28.76	36.62	64.99
1995	1.65	35.43	2.31	29.67	36.46	41.46	53.39
1997	3.30	43.56	1.46	38.79	43.43	48.70	73.46
2000	3.45	36.70	13.00	32.35	37.27	41.88	56.76
Average	2.49	36.17					

The measure is based on the quadratic vector autoregression (VAR) model and vector moving averaging (VMA) representation.[7] The trade variables include trade indicator (+1 if the trade is a purchase and −1 if a sale), signed trading volume (positive if the trade is a purchase and negative if a sale), and signed square of trade volume.[7] The VAR model is truncated at lag five and the VMA representation is truncated at lag 10. The results are reported in Table 2. In the SPDRs market, trades have an average relative informativeness of 2.49% over four sample periods. The trade informativeness for the underlying securities is about 36.17% on average. Our estimate of trade informativeness for individual stocks is comparable to the average trade informativeness of 34.3% reported in Hasbrouck (1991) based on a sample of 177 issues traded on the New York Stock Exchange. SPDRs seem to have extremely low relative trade informativeness.

Granger Causality

Granger (1969) causality measures precedence and information content between two variables. We ran the two-way test from February 1 through April 30 in 1993, 1995, 1997 and 2000. The empirical results are presented in Table 3 and Table 4.

Table 3 reports the Granger causality relationship between SPDRs quote revisions and signed trading volume. Empirical studies have shown that trade variables convey information. It is unsurprising that the signed trading volume Granger-causes quote revision overall sample periods. The coefficients on the lagged signed trading volume are all statistically significantly different from zero, i.e., quote revision can be explained better by including past values of the signed trading volume than by using only the lagged values of quote revisions.

TABLE 3
GRANGER CAUSALITY RELATIONSHIP BETWEEN QUOTE REVISION AND TRADING VOLUME FOR SPDRS

Year	Granger Causality Relationship	Test Result	
		F-statistics	P-value
1993	Signed trading volume does not granger cause quote revision	6.166	1.0E-5
	Quote revision does not granger cause signed trading volume	1.747	0.1202
1995	Signed trading volume does not granger cause quote revision	3.674	0.0025
	Quote revision does not granger cause signed trading volume	1.139	0.3373
1997	Signed trading volume does not granger cause quote revision	5.602	3.6E-5
	Quote revision does not granger cause signed trading volume	16.102	6.9E-15
2000	Signed trading volume does not granger cause quote revision	3.517	0.0035
	Quote revision does not granger cause signed trading volume	40.888	0.0000

Granger causality relationships between SPDRs quote revisions and the S&P 500 index basis are reported in Table 4. Consistent with our conjecture, we find the coefficients on the lagged index basis are all highly statistically significant. The F-statistics on the coefficient of the index basis are much higher than the F-statistics on the coefficient of signed trading volume. Overall, we conclude that the current quote revisions can be explained better by including past values of the index basis than using only the lagged values of quote revision, i.e., the index basis does convey information.

Index Basis Informativeness

We find that the S&P 500 index basis does convey more information than that conveyed by trade variables. Table 5 reports the relative informativeness conveyed by the index basis: 15.82%, 15.23%, 35.32%, and 31.44% in 1993, 1995, 1997, and 2000, respectively, compared to the 1.57%, 1.65%, 3.30%, and 3.45% conveyed by the trades and reported in Table 2.

A paired T-test is adopted to test the null hypothesis that $\mu_d = 0$ versus the alternative hypothesis $\mu_d > 0$, where $d$is basis informativeness minus trade informativeness. We compute the t-statistic as $\frac{\bar{d}}{s_d/\sqrt{n}}$, where $\bar{d}$ is the paired sample mean, s_d is paired sample standard deviation, and n is the number of pairs. A *t*-statistics of 4.6535 rejects the null hypothesis that basis informativeness is equal to trade informativeness.

TABLE 4
GRANGER CAUSALITY RELATIONSHIP BETWEEN QUOTE REVISION AND S&P 500 INDEX BASIS

Year	Granger Causality Relationship	Test Result	
		F-statistics	P-value
1993	S&P 500 index basis does not granger cause SPDRs quote revision	44.5137	0.00000
	SPDRs quote revision does not granger cause S&P 500 index basis	2.304	0.0008
1995	S&P 500 index basis does not granger cause SPDRs quote revision	80.961	0.0000
	SPDRs quote revision does not granger cause S&P 500 index basis	18.123	0.0000
1997	S&P 500 index basis does not granger cause SPDRs quote revision	342.306	0.0000
	SPDRs quote revision does not granger cause S&P 500 index basis	88.536	0.0000
2000	S&P 500 index basis does not granger cause SPDRs quote revision	818.079	0.0000
	SPDRs quote revision does not granger cause S&P 500 index basis	173.448	0.0000

TABLE 5
S&P 500 INDEX BASIS INFORMATIVENESS IN THE MARKET OF SPDRS

Year	Information Content (%)	Year	Information Content (%)
1993	15.82	1997	35.32
1995	15.23	2000	31.44

Table 6 reports the regression coefficients for the VAR model estimating index basis informativeness. The most important set of coefficients are those of B_{t-1} through B_{t-20} in the P_t equation. The coefficient for B_{t-1} is 0.4786 in the 1993 sample period. On average, the SPDRs quote midpoint in 1993 is raised by 0.4786 percent immediately after observing a one percent spread of the S&P 500 futures price over the SPDRs quote midpoint. Similar interpretations apply to the coefficients for B_{t-1} in 1995, 1997, and 2000. The coefficients at longer lags are negative but much smaller.

TABLE 6
COEFFICIENT ESTIMATES OF THE VECTOR AUTOREGRESSION MODEL (VAR) IN INDEX BASIS INFORMATIVENESS ESTIMATES

Year		a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}
1993	Coefficient	0.0269	0.0355	0.0101	0.0073	-	0.0301	0.0131	0.0064	0.0028	0.0166
	t-statistics	2.31	3.05	0.87	0.63	-0.04	2.59	1.13	0.55	0.24	1.42
1995	Coefficient	0.0687	0.0382	0.0348	0.0147	0.0164	0.0422	0.0190	0.0032	0.0227	0.0054
	t-statistics	7.75	4.28	3.89	1.65	1.83	4.70	2.11	0.35	2.53	0.60
1997	Coefficient	0.1477	0.0775	0.0628	0.0463	0.0276	0.0015	0.0137	0.0328	0.0237	0.0204
	t-statistics	27.60	14.23	11.46	8.43	5.02	0.27	2.48	5.97	4.31	3.70
2000	Coefficient	0.1678	0.0916	0.0885	0.0577	0.0395	0.0238	0.0344	0.0132	0.0083	0.0090
	t-statistics	47.08	25.33	24.36	15.82	10.83	6.51	9.40	3.61	2.27	2.46

Year		a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}	a_{17}	a_{18}	a_{19}	a_{20}
1993	Coefficient	0.0004	0.0274	0.0186	-	-	-	-	-	0.0139	0.0038
	t-statistics	0.04	2.35	1.60	-0.26	-0.53	-1.72	-0.27	-0.26	1.19	0.37
1995	Coefficient	0.0034	-	-	0.0078	-	0.0039	0.0124	-	0.0000	0.0005
	t-statistics	0.38	-0.41	-0.50	0.86	-0.29	0.43	1.38	-0.04	0.00	0.07
1997	Coefficient	0.0095	0.0139	0.0034	0.0176	0.0048	0.0113	0.0092	0.0043	0.0041	-
	t-statistics	1.73	2.53	0.62	3.20	0.88	2.06	1.68	0.78	0.75	-1.23
2000	Coefficient	0.0150	0.0087	0.0045	-	0.0056	0.0120	0.0073	0.0044	0.0129	0.0005
	t-statistics	4.09	2.37	1.22	-0.30	1.52	3.27	1.99	1.21	3.52	0.17

Year		b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
1993	Coefficient	0.4786	-	-	-	-	0.0211	-	-	-	-
	t-statistics	27.54	-6.10	-3.77	-1.89	-3.72	0.99	-1.34	-2.48	-0.52	-0.53
1995	Coefficient	0.4554	-	-	-	-	-	-	-	-	-
	t-statistics	38.51	-10.48	-3.65	-5.21	-2.84	-2.03	-2.87	-0.10	-1.16	-0.96
1997	Coefficient	0.4013	-	-	-	-	0.0007	-	-	-	-
	t-statistics	75.05	-12.55	-8.89	-6.25	-4.46	0.11	-0.41	-2.38	-1.27	-3.50
2000	Coefficient	0.3378	-	-	-	-	-	-	-	-	-
	t-statistics	110.93	-8.85	-10.71	-9.55	-6.20	-5.69	-3.24	-6.90	-2.64	-2.70

Year		b_{11}	b_{12}	b_{13}	b_{14}	b_{15}	b_{16}	b_{17}	b_{18}	b_{19}	b_{20}	$R^2(r_t)$
1993	Coefficien	-	0.043	-	-	0.002	-	0.047	-	-	-	0.096
	t-statistics	-1.49	2.06	-1.07	-2.23	0.11	-0.81	2.24	-1.60	-0.07	-0.18	
1995	Coefficien	0.014	-	0.003	0.001	-	0.013	0.002	-	0.003	0.000	0.106
	t-statistics	1.00	-0.97	0.21	0.08	-1.57	0.91	0.18	-1.67	0.21	0.04	
1997	Coefficien	-	0.005	-	-	-	-	-	-	-	-	0.180
	t-statistics	-2.22	0.83	-2.40	-2.50	-1.50	-0.63	-3.97	-0.92	-1.83	-4.32	
2000	Coefficien	-	-	-	0.003	-	-	-	-	-	-	0.185
	t-statistics	-3.42	-3.37	-2.83	0.78	-2.05	-3.20	-1.06	-3.96	-1.39	-6.69	

SUMMARY AND CONCLUSIONS

When there are informed traders in a market, new information is impounded into prices as a result of their trading. Trades usually serve as signals of information and impose a permanent impact on security prices. Hasbrouck (1991) defines current trade innovations as the signal of private information and uses VAR and VMA models to assess a proxy for information asymmetry — trade informativeness.

Although SPDRs are traded like regular stock, there is contemporaneous trading of S&P 500 index futures. Trades and basis become competing sources of information for price revisions in the SPDRs. Empirical studies have shown that trades convey information for price revisions of security. The basis conveys more information than trades for the intra-day quote price revisions in the SPDRs.

Finally, we extend the Hasbrouck (1991) informativeness estimates by including the S&P 500 index basis instead of trade variables. Over four sample periods, the basis explains 24% of permanent price change in SPDRs, while only 2.5% is attributable to trades. Our findings are consistent with the price revision process in that the basis transmits innovative information from futures prices and induces permanent price changes in the SPDRs. This study documents the essentials of futures trading in designing an active index-tracking market.

ENDNOTES

1. Index-tracking stocks with large trading volume always have futures contracts traded on the same underlying index portfolio. The top three index-tracking stocks in the U.S. markets are Qubes (based on the Nasdaq 100 index), SPDRs, and DIAMONDs (based on Dow Jones 30 index). All three index-tracking stocks have futures counterparts traded on the markets.
2. As exchange-traded fund (ETF) products have attracted considerable trading volume in the U.S. markets, stock exchanges all over the world have begun to trade their own ETF products. TraHK tracks the Hong Kong Hang Seng index; iFTSE100 represents the FTSE100. A policy question raised by regulators is whether to introduce a corresponding futures contract. An example occurred in Taiwan. The Taiwan 50 Index (an ETF product) and its corresponding futures contract began to be simultaneously traded on June 30, 2003.
3. Price level for SPDRs is about one tenth of S&P 500 index level. A $1/32 price change in SPDRs is equivalent to a change of 0.3125 index point. The minimum tick size changed to one penny in 2001.
4. A footnote in the S&P's Quarterly Dividend Record Issue indicates the dividends per share on S&P Indexes are computed by multiplying the monthly average of the S&P 500 Daily Stock Index by the monthly average of the weekly dividend yield (%), the latter series based on indicated annual dividend yields.
5. In Hasbrouck (1991), VAR is truncated at lag 5. We choose lag 20 instead of lag 5 because there is little change in the index basis informativeness estimations when we increase it from 20 to 30, but there is a significant increase when we increase the lag from 5 to 20.
6. See Hasbrouck (1991) Equation (4) ~ (7).
7. Following Lee and Ready (1991), we classify the trades that occur in the middle of the spread using the tick test and other trades as buys (sells) if they are closer to the ask (bids). We compare the trades with their most recent quotes. The most recent quotes are defined as the quotes that were time stamped at least five seconds before the trades.

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