HAS THE INTRODUCTION OF S&P 500 ETF OPTIONS LED TO IMPROVEMENTS IN PRICE DISCOVERY OF SPDRs?

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This study sets out to investigate trading in Standard and Poor's Depository Receipt Trust Series I (SPDR) options and the impact on the price-discovery process of SPDRs. The empirical results reveal a significant rise in liquidity within the SPDR market following the introduction of SPDR options. Furthermore, the results also show that the introduction of SPDR options has led to a significant improvement in the information share of SPDRs, and that the contribution of SPDRs to price discovery has become very close to that of E-mini index futures. These findings imply that developments in the derivatives market can lead to improvements in market quality, including the level of liquidity and price discovery of the underlying securities. © 2011 Wiley Periodicals, Inc. Jrl Fut Mark 32:683–711, 2012

The authors thank Robert Webb (the Editor), Wen-Liang Hsieh, Tsung-Wu Ho, and especially an anonymous referee for their helpful comments and suggestions. The financial supports provided by the National Science Council of Taiwan and the MoE ATU plan of National Chiao Tung University are also gratefully acknowledged. Any errors are the sole responsibility of the authors.

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Received April 2011; Accepted May 2011

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The Journal of Futures Markets, Vol. 32, No. 7, 683–711 (2012)

Published online July 5, 2011 in Wiley Online Library (wileyonlinelibrary.com)
DOI: 10.1002/fut.20538

1. INTRODUCTION

Standard and Poor's Depository Receipts Trust Series I (SPDRs) were first listed on the American Stock Exchange (AMEX) on January 29, 1993, and have since become the most active 'exchange traded funds' (ETFs). On January10, 2005, trading in SPDR options began on the Chicago Board Options Exchange (CBOE) hybrid trading system. Both efficiency and quality in the SPDR market would be enhanced by the introduction of this new derivative, essentially because market participants could actually replicate certain trading strategies using these tradable instruments.[1]

In the current study, we analyze the impact of the introduction of SPDR options on the contribution to the price-discovery process of SPDRs. Although many studies have been undertaken on derivatives trading, and the resultant influence on the market quality of the underlying assets, very few have examined the impact of derivatives trading on price discovery of the underlying assets. This is, nevertheless, an important topic, since the introduction of derivatives trading may have significant impacts on the market quality of the underlying security, which ultimately affects the contribution made by the underlying security to the overall process of price discovery.

A variety of authors have investigated the price-discovery process for S&P 500 index derivatives. Chu, Hsieh, and Tse (1999) and Hasbrouck (2003), analyzing the issue of price discovery for S&P 500 index derivatives, indicate that most of the price discovery is contributed by S&P 500 index futures, with SPDRs playing an insignificant role on the price-discovery process within the S&P 500 index market. Tse, Bandyopadhyay, and Shen (2006) subsequently argue that the primary explanatory reason for the prior findings, that SPDRs provided no significant contribution to price information, was the 'electronic communications network' (ECN) platform examined in the prior studies.[2] Although Tse et al. (2006) demonstrate that E-mini futures contribute the most to price discovery, the contribution to price discovery by electronically-traded ETFs on the Archipelago (ArcaEx) ECN was found to be higher than in

[1]The Chicago Mercantile Exchange (CME) also announced the launch of futures contracts on June 20, 2005 on three of the largest and most actively traded ETFs in the United States, with trading in the new CME ETF futures contracts on SPDRs subsequently taking place on the exchange's CME Globex electronic trading platform. One of the advantages of ETF futures, like all futures, is that they allow investors to take a short position without borrowing shares from a broker, which is necessary to short sell securities or ETFs. Furthermore, the initial margin with ETF futures will generally be lower than the Regulation T margins associated with the underlying ETF.

[2]ECNs are electronic trading systems that automatically match buy and sell orders at specified prices without having to go through any intermediaries. They feature fast and efficient trade execution, lower transaction costs and trader anonymity.

the prior studies, indicating that ETFs play a significant role in the price-discovery process.[3]

According to the results of the aforementioned studies, S&P 500 index E-mini futures still dominate SPDRs, although a gradual rise has become discernible in the contribution to price discovery made by SPDRs traded on ECNs. Tse et al. (2006) suggest that ECNs offer the advantages of both anonymity and speed of execution, both of which can attract informed investors to trade in SPDRs. Since the introduction of derivatives trading also affects the trading of informed investors on the underlying securities, this raises the main question as to whether S&P 500 ETFs have provided a greater contribution to price discovery from the introduction of S&P 500 ETF options onwards.

Further, considerable concern has arisen within the prior literature over the past few decades with regard to the impact of derivatives trading on the market quality of the underlying securities. These works can essentially be classified under two distinct themes: whether trading in derivatives has a beneficial or harmful effect on the market of the underlying securities.[4]

For example, some studies argue that due to the higher degree of leverage, derivatives markets tend to attract uninformed speculative investors, and thus, destabilize the underlying asset markets through the increase in volatility; these studies contend that derivatives encourage speculation, thereby causing destabilization of the spot markets (see, for example, Conrad, 1989; Cox, 1976; Figlewski, 1981; Harris, Sofianos & Shapiro, 1994; Rahman, 2001). Conversely, other studies argue that since the derivatives markets increase the overall market quality and informativeness, this may well reduce the overall volatility of the underlying securities through the transfer of risk (see, for example, Danthine, 1978; Powers, 1970; Schwartz & Laatsch, 1991).

From their examination of the impact of stock options listings on various aspects of the market quality of the underlying stock, Kumar, Sarin, and Shastri (1998) found discernible reductions in the spread along with increases in quoted depth, trading volume, trading frequency and transaction size after options listings. Their empirical findings suggest that options listings improve the market quality of the underlying stocks. Further, de Jong, Koedijk, and Schnitzlein (2006) suggest that the presence of listed options is associated with the high quality of the underlying asset market, since they argue that if market makers

[3]Tse et al. (2006) argue that the prior research result, i.e., ETFs play an insignificant role in the price-discovery process, is surprising because ETFs are traded actively and have low transaction costs. Therefore, they suggest that this possible anomaly is due to informed traders' preference for electronic trading markets over floor trading markets.

[4]Danielsen, Van Ness, and Warr (2007) provide another viewpoint, which is that the options do not systematically improve the market quality of the underlying security, but rather that the market quality of the underlying security is improved prior to the listing decision.

in the stock learn from transactions in the option, they can ultimately set a more accurate price.

According to the extant literature, there are three possible explanations as to why the introduction of derivatives may improve the contribution to price discovery by the underlying securities (see Chakravarty, Gulen, & Mayhew, 2004; de Jong et al., 2006; Fleming, Ostdiek, & Whaley, 1996; Kumar et al., 1998). First, derivatives markets can improve the efficiency of incomplete asset markets by expanding the opportunity set that market participants are faced with (Hakansson, 1982; Ross, 1976). Arbitrageurs can easily replicate arbitrage trading strategies by simultaneously using both the derivatives and the underlying securities.[5] Second, derivatives trading may improve the efficiency of the underlying market by increasing the level of public information within the market (Kumar et al., 1998). As such, informed traders usually trade simultaneously in both the underlying security and derivatives markets in order to exercise certain trading strategies (Chakravarty et al., 2004). Thirdly, if the market makers in the underlying security learn from the transactions that transpire in derivatives markets, they can ultimately set a more accurate price in the market of the underlying asset (de Jong et al., 2006).

The process of price discovery is influenced by many factors, including market depth, trading volume, bid-ask spread and market volatility. Several theoretical hypotheses indicate that markets with greater liquidity, lower transaction costs and fewer restrictions are likely to play more important roles in terms of price discovery.[6] The prior studies demonstrate that the introduction of derivatives trading has significantly improved the market liquidity of the underlying securities;[7] however, such improvement in the market liquidity would have simultaneously led to an increase in the contribution to price discovery made by the underlying securities. It is therefore surmised that as a result of the introduction of SPDR options, SPDRs now make a greater contribution to the share of information.

Several studies have investigated the impact of options trading on the market quality of the underlying securities (Danielsen et al., 2007; de Jong et al., 2006; Kumar et al., 1998); however, the current study differs from the extant literature in several ways. Firstly, Chakravarty et al. (2004) investigate the contribution of options markets to price discovery using the 'information share'

[5]Richie, Daigler and Gleason (2008) demonstrate that the limited volume size is the key arbitrage limitation for SPDRs; as such, arbitrage between SPDRs and SPDR options cannot be replaced by arbitrage between the S&P 500 index futures and SPDR options.

[6]Chu et al. (1999) summarize the four main hypotheses (leverage, trading cost, uptick rule and market-wide information hypotheses) to explain the preferences of informed traders according to different market structures and security designs.

[7]Kumar et al. (1998) note that the bid-ask spread, quoted depth and information efficiency all improved for the underlying securities as a result of the introduction of options trading; however, they do not discuss the issue of the contribution to price discovery by the underlying securities.

approach. Although they argue that stock options trading directly contributes to price discovery in the underlying stock market, there is no empirical evidence in the change of price discovery for the underlying stocks in their study.

Second, as compared with the prior studies (Chu et al., 1999; Hasbrouck, 2003; Tse et al., 2006), this study focuses on the four venues–AMEX, Island ECN, ArcaEx ECN and NASDAQ—which account for over 95% of all transactions in the SPDR market. The analysis of the four venues explains how SPDR options affect the improvement in the contribution to price discovery, whether it is due to the market competition (the AcaEx ECN) or the product competition (the overall SPDR market).

Third, the present study differs from de Jong et al. (2006), in which an experimental approach was used to compare a market with a traded option with a market operating in isolation. In comparison, the 'permanent-transitory' 'information share' and 'modified information share' MIS (Lien & Shrestha, 2009) approaches are used in this study to measure the level of price discovery across the SPDR market. The MIS approach provides a unique measure of price discovery, which is independent of the ordering of variables in the Cholesky factorization of the innovation covariance matrix.

The empirical results reveal that the introduction of SPDR options has led to an increase in both market liquidity and price discovery of SPDRs. According to the 'transaction cost' hypothesis, those securities with lower trading costs contribute a higher level of price discovery; it is therefore argued that as a result of the introduction of derivatives, the benefits obtained by market participants, essentially as a result of improved liquidity, have led to a reduction in implicit trading costs. This is attributable to either a reduction in the bid-ask spread or an increase in quoted depth, ultimately leading to SPDRs contributing a greater information share to price discovery.

This analysis further reveals that SPDRs traded electronically on the ArcaEx ECN dominate the price discovery process for SPDR shares, with the contribution to price-discovery being very close to E-mini futures, thereby indicating that SPDRs and E-mini futures possess equal importance in the price-discovery process of the S&P 500 index market. The empirical results also show that the leverage effect is significant during high-volatility periods. The main implication of these findings is that developments in the derivatives markets provide valuable improvements in market quality for the underlying securities, both in terms of liquidity and price discovery.

The remainder of this study is organized as follows. A description of the data is provided in Section 2, followed in Section 3 by a discussion of the research methodology. Section 4 presents the empirical results pertaining to the change in the contribution to price discovery made by SPDRs. Finally, conclusions drawn from this study are presented in Section 5.

2. DATA DESCRIPTION

The sample for this study is comprised of SPDRs, S&P 500 index regular futures and E-mini futures. The SPDR prices are usually scaled down in order to make them comparable to stock prices; thus, the SPDR prices are set at one-tenth of the S&P 500 index level. The sample covers the period from February 25, 2004 to November 23, 2005, a 22-month period that begins approximately 11 months prior to the date of the introduction of SPDR options (January 10, 2005) and ends approximately 11 months after their introduction.

The tick-by-tick data on the S&P 500 index are obtained from the Tick Data database, whereas the SPDRs data, which includes the tick-by-tick quote as well as the trade prices, trading volume, quoted depth and bid-ask spread, are obtained from the NYSE Trade and Quote (TAQ) database. This study retains only those trades and quotes that occurred during regular trading hours between 9:30 a.m. and 4:00 p.m., EST. The corresponding data on regular and E-mini index futures, which include the trade prices and number of trades, are obtained from the Tick Data intraday database, while the data on futures are obtained from the Chicago Mercantile Exchange (CME), and cover the trading hours from 8:30 a.m. to 3:00 p.m., CST.

A comprehensive introduction to the market structures of index futures and ETFs has already been provided in many prior studies.[8] Briefly, S&P 500 index regular futures are traded on the open-outcry floor of the CME, whereas S&P 500 index E-mini futures are traded on the CME's electronic platform. The regular futures and E-mini futures are similar in many ways. For example, both contracts have the same underlying cash index, the same expiration date and time and the same settlement price, among other similarities. The main differences between the E-mini and regular futures contracts are the contract size and trading hours. The E-mini futures contract multiplier is one fifth of the regular futures contract multiplier. In addition, E-mini futures contracts are traded electronically and are available nearly 24 hours per day. As such, E-mini futures are designed for individual or small investors.

ETFs are listed on the AMEX; however, trading in ETFs takes place in multiple venues. On July 31, 2001, the NYSE began trading the three most active ETFs, the NASDAQ-100 Trust Series I, the Standard and Poor's Depository Receipt Trust Series I and the Dow Jones Industrial Average Trust Series I, all listed on the AMEX on an 'unlisted trading privilege' (UTP) basis.[9]

[8]See for example Tse and Erenburg (2003), Tse and Hackard (2004), Hendershott and Jones (2005a, 2005b), Ates and Wang (2005), Tse et al. (2006), Nguyen, Van Ness, and Van Ness (2007) and Bandyopadhyay, Martinez, and Tse (2009).

[9]An UTP is a right provided by the Securities Exchange Act of 1934 which permits securities listed on any national securities exchange to be traded by other such exchanges.

Under the UTP framework, a stock listed on the AMEX can also trade on other exchanges without a dual listing. Various studies subsequently provide evidence of the impact of the UTP system on market quality. For example, Boehmer and Boehmer (2003) and Tse and Erenburg (2003) investigate the entry of the NYSE on the ETF market. They show a dramatic improvement in liquidity due to the elimination of market maker rents, and that the competition within multi-market trading improves market quality with regard to reduced spreads and greater price discovery.

Although the primary listing exchange for SPDRs is the AMEX, the majority of the trading volume and transactions come from ECNs such as ArcaEx and Island. Huang (2002) and Barclay, Hendershott, and McCormick (2003) focus on the role and impact of ECNs on NASDAQ trading. They suggest that the main advantages of trading in ECNs are the rapid and efficient execution of trades and the anonymity of traders, which together attract more informed traders to trade on ECNs resulting in better price discovery. The property of trader anonymity is not available for NASDAQ traders. The dominant trading platform for the major ETFs was the Island ECN up until September 2002, when it stopped displaying its limit order book; this lack of information display led to reduced volumes and higher transaction costs (Hendershott & Jones, 2005a). In turn, a considerable proportion of the market share of the Island ECN subsequently migrated to the ArcaEx ECN, such that their market share more than doubled (Tse & Hackard, 2004). When the Island ECN later chose to redisplay its orders, it was no longer a dominant player in this market. Tse et al. (2006) summarize the two previous studies to show that the ETFs traded on the ArcaEx ECN relatively dominated the price-discovery process for ETF shares in 2004.

Comprehensive details on the number of trades, trade size and transactions by trade size within different trading centers are reported in Table I. This table depicts the number of transactions and trading volumes of SPDRs on nine trading venues including: the AMEX (A, the exchange code in TAQ data), the Boston Stock Exchange (B), the Cincinnati Stock Exchange (C), the Chicago Stock Exchange (M) the NYSE (N), the Pacific Stock Exchange (P), the NASDAQ (T), the Chicago Board of Options Exchange (W), and the Philadelphia Stock Exchange (X). In 2005, over half of the SPDR volume was traded on ECNs.

Table I also shows that in the second sample period, the growth in total transactions and trading volume was close to 65% and 40%, respectively. This result indicates that trading activities have increased significantly in the SPDR markets following the introduction of SPDR options trading. In addition, Table I shows that over 95% of all transactions are concentrated on four exchanges in the first and second periods: the AMEX (A), Cincinnati (C), Pacific (P) and

TABLE I

Number of Transactions and Trading Volume for SPDRs in Different Trading Centers

Trading Centers	Trades		Trading Volume		Transactions by Trade Size (No. of Shares)					
	Total No.	%	Total No. (×100 Shares)	%	Small Size (≤1,000)	%	Medium Size (1,001–9,999)	%	Large Size (≥10,000)	%
Panel A: First period (February 25, 2004–January 7, 2005, 220 trading days)										
A (AMEX)	449,526	3.73	11,079,178	12.24	283,735	2.60	141,314	13.42	24,477	29.69
B (Boston)	124,926	1.04	10,69,220	1.18	106,050	0.97	18,095	1.72	781	0.95
C (Cincinnati)	3,890,510	32.25	29,393,969	32.48	3,341,028	30.57	536,587	50.97	12,895	15.64
M (Chicago)	73,183	0.61	631,553	0.70	63,976	0.59	8,649	0.82	558	0.68
N (NYSE)	190,966	1.58	4,000,786	4.42	153,561	1.41	29,777	2.83	7,628	9.25
P (Pacific)	6,859,987	56.87	20,861,891	23.05	6,589,482	60.30	260,036	24.70	10,469	12.70
T (NASDAQ)	443,032	3.67	22,830,184	25.22	366,053	3.35	52,417	4.98	24,562	29.79
W (CBOE)	5,769	0.05	439,091	0.49	2,453	0.02	2,399	0.23	917	1.11
X (Philadelphia)	24,764	0.21	200,968	0.22	21,166	0.19	3,447	0.33	151	0.18
Total	12,062,663	100.00	90,506,840	100.00	10,927,504	100.00	1,052,721	100.00	82,438	100.00
Panel B: Second period (January 10, 2005–November 23, 2005, 220 trading days)										
A (AMEX)	506,656	2.55	9,885,202	7.82	366,647	1.99	121,117	8.47	18,892	21.26
B (Boston)	106,232	0.53	937,372	0.74	89,163	0.49	16,364	1.14	705	0.79
C (Cincinnati)	6,959,797	34.97	37,083,839	29.33	6,314,937	34.35	630,372	44.06	14,488	16.30
M (Chicago)	128,146	0.64	884,854	0.70	121,358	0.66	6,174	0.43	614	0.69
N (NYSE)	168,650	0.85	325,7116	2.58	130,590	0.71	30,916	2.16	7,144	8.04
P (Pacific)	9,349,067	46.98	32,474,709	25.68	8,916,748	48.51	416,464	29.11	15,855	17.84
T (NASDAQ)	2,674,821	13.44	41,149,130	32.54	2,439,085	13.27	206,467	14.43	29,269	32.93
W (CBOE)	7,760	0.04	781,585	0.62	2,967	0.02	2,884	0.20	1,909	2.15
Total	19,901,129	100.00	126,453,807	100.00	18,381,495	100.00	1,430,758	100.00	88,876	100.00

Note. This table presents the transactions and trading volumes of SPDRs on nine trading venues including the AMEX (A, the exchange code in TAQ data), the Boston Stock Exchange (B), the Cincinnati Stock Exchange (C), the Chicago Stock Exchange (M), the NYSE (N), the Pacific Stock Exchange (P), the NASDAQ (T), the Chicago Board Options Exchange (W) and the Philadelphia Stock Exchange (X).

NASDAQ (T). In particular, 56% (46%) of all transactions in the first (second) period are attributable to the Pacific Exchange. Clearly, therefore, the Pacific Exchange may be responsible for most of the information on SPDR prices.

Consistent with prior studies (Hendershott & Jones, 2005a, 2005b; Tse & Erenburg, 2003), this study defines small-sizes trades as those consisting of 1–1,000 shares, medium-sized trades as 1,001–9,999 shares, and large-sized (block) trades as 10,000 shares or greater. From observations of the size distribution of transactions during the first period, we find that the Pacific Exchange accounts for 68% of small trades, the Cincinnati Exchange accounts for 55% of medium-sized trades and the NASDAQ accounts for 28% of block trades. Following the introduction of options trading, these three exchanges remain the most active in terms of small, medium and block trades. This result is also consistent with the finding of Nguyen et al. (2007), who found that the ECN mean trade size within the ETF market is small, and that large trades usually occur in traditional markets such as the NASDAQ, AMEX and NYSE.

The Pacific Exchange created a coalition with the ArcaEx ECN in 2003 to provide the exchange with the ability to electronically trade listed securities; the Island ECN also started to report its trades through the Cincinnati Stock Exchange in the same year. Therefore, this study adopts the Pacific Exchange data for the ArcaEx ECN and the Cincinnati Exchange data for the Island ECN. Although the current study covers all of the exchanges in the TAQ database, the examination of price discovery for SPDR trades and quotes focuses on a sample of SPDRs traded on the AMEX, Island ECN, ArcaEx ECN and NASDAQ. As shown in Table I, these four exchanges accounted for approximately 93% of the total trading volume in the first period and 95% of the total trading volume in the second period. Therefore, this investigation of the four venues also provides insights into whether the improvement in the contribution to price-discovery stems from the ArcaEx ECN or the overall SPDR market.

In order to ensure the accuracy of the sample data, all trades and quotes that are out of time sequence are deleted, while quotes meeting any of the following three conditions are also discarded: (i) either the bid or the ask price is equal to or less than zero; (ii) either the bid or the ask size is equal to or less than zero and (iii) either the price or the volume is equal to or less than zero. Data errors are further minimized by eliminating trades and quotes meeting the criteria outlined in Hasbrouck (2003). All quotes are screened to remove zero and negative spreads, and spreads greater than one dollar. In addition, the trades are screened for outliers using a filter that removes prices that differed by more than 10% from the last prices, i.e., $|(P_t - P_{t-1})/P_{t-1}| > 0.1$.

3. RESEARCH METHODOLOGY

3.1. Measurement of Price Discovery

For those securities trading in multiple venues, price discovery plays an important role in determining the dominant market by identifying new equilibrium prices. Within the prior literature on common factor models, two popular approaches have emerged within the investigation of the mechanics of price discovery: the PT model discussed by Gonzalo and Granger (1995), and the 'information shares' (IS) model developed by Hasbrouck (1995). Although both models are based on the 'vector error correction model' (VECM), different definitions of price discovery are adopted in each model.

The PT and IS models have attracted considerable attention within the literature, where the relationships and differences between the two models have been discussed at length. The Gonzalo and Granger (1995) model focuses on the common factor components and the process of error correction, whereas the Hasbrouck (1995) model considers the contribution of each market to the variance in the innovations to the common factor. For an overview of the various price-discovery issues, refer to Baillie, Booth, Tse, and Zabotina (2002), Hasbrouck (2002), de Jong (2002), Lehmann (2002) and Harris, McInish and Wood (2002a, 2002b).

These two models are directly related and provide similar results if the residuals are uncorrelated between markets; however, they typically provide quite diverse results in those cases where there is substantive correlation. Numerous studies have adopted the two models as the means of examining the price-discovery contribution from closely related markets (see Booth, So, & Tse, 1999; Chu et al., 1999; Hasbrouck, 2003; So & Tse, 2004). The analysis is based on the information share approach which requires the estimation of the VECM. According to Engle and Granger (1987), the representation of the VECM can be shown as follows:

$$\Delta Y_t = \mu + \Pi Y_{t-1} + \sum_{i=1}^{k} A_i \Delta Y_{t-i} + \varepsilon_t \tag{1}$$

where $\Pi Y_{t-1} = \alpha\beta' Y_{t-1} = \alpha z_{t-1}$; Y_t is an $n \times 1$ vector of cointegrated prices; A_i represent $n \times n$ matrices of autoregressive coefficients; k is the number of lags; $z_{t-1} = \beta' Y_{t-1}$ is an $(n-1) \times 1$ vector of error correction terms; α is an $n \times (n-1)$ matrix of adjustment coefficients; and ε_t is an $n \times 1$ vector of price innovations.

The coefficient α's of the error correction term measure the price reaction to the deviation from the long-run equilibrium relationship. The current study follows Hasbrouck (1995, 2003) for the definition of z_t; if there are n securities, then there are $n - 1$ linearly independent differences, and thus, z_t can be defined as:

$$z_t = [(Y_{1t} - Y_{2t}) \quad (Y_{1t} - Y_{3t})] \quad \ldots \quad (Y_{1t} - Y_{nt})]' \tag{2}$$

3.1.1 Measurement of permanent-transitory (PT) decomposition

The Gonzalo and Granger (1995) study focuses on the error correction process, which involves only permanent (as opposed to transitory) shocks resulting in disequilibrium. The measure is based on the PT decomposition, where the permanent component is assumed to be a linear function of the original series. The PT model measures the contribution to the common factor for each market, where the contribution is defined as a function of the error correction coefficients of the markets. Stock and Watson (1988) demonstrated that the price vector can be decomposed into permanent and transitory components. Accordingly, the common trend of the price series is as follows:

$$Y_t = f_t + G_t \tag{3}$$

where f_t is the common factor, and G_t is the transitory component that has no permanent impact on Y_t. Gonzalo and Granger (1995) decompose the common factor f_t into a linear combination of the prices, in which $f_t = \Gamma' Y_t = (\alpha'_{\perp}\beta_{\perp})^{-1}\alpha'_{\perp}Y_t$, where Γ is the common factor coefficient vector, Γ are normalized so that their sum is equal to 1, and the coefficients of Γ_i can be interpreted as portfolio weights (de Jong, 2002). In this study, we follow the approach proposed by Gonzalo and Ng (2001) for the estimation of $\alpha_{\perp}$ and $\beta_{\perp}$.[10]

Briefly, the common factor framework provides an opportunity to examine the extent to which each market is involved in the price-discovery process, with the advantage of the Gonzalo and Granger (1995) model being that the common factor estimates are identified exactly, since they are not dependent on the ordering of the variables. However, the common factor weights may be negative for each estimated VECM.

3.1.2. Measurement of information share (IS)

The IS model measures the relative contribution of each market to this variance; this contribution is then referred to as the information share of that particular market. The process of price discovery is analyzed using the Hasbrouck

[10]Gonzalo and Ng (2001) provide three methods for the calculation of $\alpha_{\perp}$. The method used in the current study is to calculate the eigenvector associated with the smallest eigenvalues of the matrix $\alpha\alpha'$; this eigenvector is the estimator of $\alpha_{\perp}$. Furthermore, from the definition of z_t, $\beta_{\perp} = I$, where I is an $n \times 1$ vector of ones.

(1995) model, which calculates ‘information shares’ as the relative contributions of the variance of a security to the overall variance in the innovations of the unobservable efficient price. According to Hasbrouck (1995), the efficient price, v_t, follows a random walk: $v_t = v_{t-1} + u_t$. The observed prices of several cointegrated markets contain the same random walk component, as well as components incorporating the effects of market friction.

In contrast to the PT model, Hasbrouck (1995) transforms the VECM into a vector moving average (VMA) model, which is represented as follows:

$$\Delta Y_t = \psi(L)\varepsilon_t \tag{4}$$

along with its integrated form:

$$Y_t = Y_0 + \psi(1)\sum_{i=1}^{t}\varepsilon_i + \psi^*(L)\varepsilon_t \tag{5}$$

where Y_t is the vector of the price series; ε_t is a zero-mean vector of serially uncorrelated innovations with covariance matrix Ω , such that σ_i^2 is the variance in ε_{it}, and ρ_{ij} is the correlation between ε_{it} and ε_{jt}. Furthermore, t is a column vector of ones, ψ is a row vector, and $\psi(L)$ and $\psi^*(L)$ are matrix polynomials in the lag operator L.

Hasbrouck (1995) notes that the common factor innovation in Equation (5) is the increment, $\psi\varepsilon_t$, with the price change component permanently impounded into the price. He demonstrates that Equation (5) is closely related to Equation (3). In addition, he further decomposes the variance in the innovations in the common factor, $Var(\psi\varepsilon_t) = \psi\Omega\psi'$, and defines the information share of a trading center as the proportion of $Var(\psi\varepsilon_t)$ attributable to the innovations in that market.

Hasbrouck (1995) uses the Cholesky factorization of $\Omega = FF'$ to eliminate the contemporaneous relationship, where F is a lower triangular matrix. The information shares are then given as:

$$IS_j = \frac{([\psi F]_j)^2}{\psi\Omega\psi'}, \quad j = 1, 2, \ldots, n \tag{6}$$

where $[\psi F]_j$ is the j^{th} element of the row of matrix ψF.[11] The contribution to price discovery by a particular market is measured as its relative contribution to the variance of the innovation in the common trend.

[11]It should be further noted that Baillie et al. (2002) present evidence of the existence of an important relationship between $\psi = (\psi_1, \psi_2, \ldots, \psi_n)$ and $\Gamma = (\gamma_1, \gamma_2, \ldots, \gamma_n)$, i.e., $\psi_i/\psi_j, = \gamma_i/\gamma_j$. This relationship is substituted into Equation (6) to calculate the information share.

Baillie et al. (2002) demonstrate a simpler method of calculating information shares directly from the VECM results without obtaining the VMA representation, with the calculations of information share based on the VECM method. The upper and lower bounds of the information share of a market will, however, become apparent when the variables are given different orderings, with the largest (smallest) information share value occurring when the variable is first (last) in a sequence, assuming that the cross-correlation, ρ, is positive. This relationship also indicates that the higher the correlation, the greater (smaller) the upper (lower) bound. Baillie et al. (2002) therefore propose the use of the mean of the bounds to resolve such interpretational ambiguity.

3.1.3 Measurement of Modified Information Share (MIS)

The results of the information shares are typically dependent on the ordering of the variables in the Cholesky factorization of the innovation covariance matrix. The first (last) variable in the ordering tends to have a higher (lower) information share, with this discrepancy potentially being substantial if the innovations of the series are highly and contemporaneously correlated.

Lien and Shrestha (2009) propose a MIS approach that leads to a unique measure of price discovery, as opposed to upper and lower IS bounds. When adopting the MIS model, it is suggested that the factorization matrix (based on the correlation matrix) be used. Lien and Shrestha (2009) further define Φ as representing the innovation correlation matrix and Λ as representing the diagonal matrix, with the diagonal elements being the eigenvalues of the correlation matrix Φ, where the corresponding eigenvectors are given by the columns of matrix G. In addition, V is a diagonal matrix containing the innovation standard deviations on the diagonal—that is, $V = \text{diag}(\sqrt{\Omega_{11}}, \ldots, \sqrt{\Omega_{nn}})$. Lien and Shrestha (2009) subsequently transform $F^* = [G\Lambda^{-1/2}\, G'V\cdot^{-1}]^{-1}$ from $\Omega = F^*(F^*)'$. Under this factor structure, the MIS is given by:

$$IS_j^* = \frac{\psi_j^{*2}}{\psi\Omega\psi'} \tag{7}$$

where $\psi^* = \psi F^*$. Under this new factor structure, Lien and Shrestha (2009) show that the resultant IS are independent of ordering, which leads to a measure of price discovery that is order invariant, but not unique. Based on their use of the square-root matrix, they indicate that this solves the problem of the lack of uniqueness. In addition, they also show that the MIS measure outperforms both the IS measure and the PT measure.

3.2. Regression Model

The empirical methodologies have thus far tended to focus on the contribution of SPDRs to price discovery; however, the change in price discovery for SPDRs may have been affected by changes in market factors beyond the introduction of SPDR options. Thus, we follow Chakravaty et al. (2004) and Ates and Wang (2005) to control for other factors, by first of all examining the change in the market liquidity of SPDRs. This study also adopts the market quality index (*MQI*), which, according to Bollen and Whaley (1998), is defined as the ratio of the average share depth at the prevailing bid and ask price quotes to the percentage quoted spread:

$$MQI = \frac{(Q_{bid} + Q_{ask})/2}{(P_{ask} - P_{bid})/[(P_{ask} + P_{bid})/2]} \tag{8}$$

where P_{ask} is the ask price, P_{bid} is the bid price, Q_{ask} is the depth at ask, and Q_{bid} is the depth at bid.

Bollen and Whaley (1998) use this measure to consider changes in the trade-off between the quoted spread and market depth; as such, the *MQI* represents a measure of market liquidity. Following the introduction of SPDR options, any inferences to improvements in the contribution made to price discovery by SPDRs may well be affected by changes in market liquidity over the sample period. Therefore, this study follows Bollen and Whaley (1998) by adopting a dummy variable, along with trading volume and market volatility, all of which are employed as control variables in order to determine the improvements in the market liquidity of SPDRs as a direct result of the introduction of SPDR options. We investigate the change in the *MQI* following the introduction of SPDR options using a regression model as defined in the following equation:

$$\log(MQI_t) = \alpha_0 + \alpha_1 D_t^{Opt} + \alpha_2 \log(Vol_t) + \alpha_3 \sigma_t + \varepsilon_t \tag{9}$$

where t denotes the daily time interval; MQI_t is the market quality index of SPDRs during trading day t; D_t^{Opt} is a dummy variable that is equal to 0 for those options in the pre-listing period, and 1 thereafter; Vol_t is the trading volume of SPDRs during trading day t and σ_t is the Parkinson (1980) extreme value estimator that proxies for the volatility of the S&P 500 index market.

According to the arguments of Stoll (1978) and Bollen and Whaley (1998), a higher daily trading volume will lead to a lower margin requirement by market makers to cover the fixed costs of their operations due to the faster transaction time rates. Furthermore, greater volatility will lead to a greater likelihood of an adverse price move during the time that the stock is in the market maker's inventory, resulting in a greater spread. Therefore, it is expected that in

Equation (9), the coefficients on both the dummy variable and trading volume will be positive, whereas the coefficient on volatility will be negative.

This study also investigates the change in price discovery for SPDRs. Chakravaty et al. (2004) argue that price discovery is related to trading volume, spread and volatility. We can consider the change in the level of price discovery after the introduction of derivatives by using a regression model, as defined in the following equation:

$$PD_t = \beta_0 + \beta_1 D_t^{Opt} + \beta_2 \log(Vol_t/Vol_{t-1}) + \beta_3 \sigma_t + \varepsilon_t \tag{10}$$

where t denotes the daily time interval; PD_t denotes the daily share of information for the SPDRs measured by the PT, IS and MIS models for SPDR trades on an venue and compared with E-mini futures prices, D_t^{Opt} is a dummy variable that is equal to 0 for those options in the pre-listing period, and 1 thereafter; $\log(Vol_t/Vol_{t-1})$ is the rate of change in the trading volume of SPDRs during trading day t; and σ_t is the Parkinson (1980) extreme value estimator that proxies for the volatility of the S&P 500 index market.

In order to provide additional support for the argument that the improvement in the contribution of SPDRs to price discovery is caused by enhancements to market liquidity, the *MQI* is added into Equation (10) and defined as follows:

$$PD_t = \beta_0 + \beta_1 D_t^{Opt} + \beta_2 \log(Vol_t/Vol_{t-1}) + \beta_3 \sigma_t + \beta_4 \log(MQI_t) + \varepsilon_t \tag{11}$$

where MQI_t is the market quality index for SPDRs during trading day t. The dummy variable D_t^{Opt} is also included in the regression to test for the structural shift in the level of price discovery following the introduction of SPDR options. Since both market liquidity and price discovery may be determined simultaneously following the introduction of SPDR options,[12] Equation (11) is estimated using the two-stage least-squares (2SLS) approach, which employs the lagged *MQI*, lagged market volatility, and previous day's trading volume as the instrument variables for the *MQI*.

A significantly positive coefficient on the dummy variable is expected prior to considering the *MQI* variable. If market liquidity improves as a result of the introduction of SPDR options, then this indicates a reduction in market impact costs; as such, any significantly positive coefficient on the dummy variable will be diluted due to the rising liquidity after considering the *MQI* variable. A significantly positive coefficient on the rate of change in trading volume is also expected.

[12]Bloomfield, O'Hara, and Saar (2005) explain why electronic markets can endogenously create liquidity even in the presence of information asymmetry. They show that informed traders take liquidity when the value of their information is high and provide liquidity when the value of their information is low. As such, the improvement in liquidity also implies the possibility that more informed traders are participating in the SPDR market since the introduction of SPDR options.

Regarding the impact of market volatility on price discovery, it is argued in some prior studies (see Capelle-Blancard, 2001; Chakravaty et al., 2004; Chen & Gau, 2009) that in those cases where there is a higher level of uncertainty in the underlying market, a greater (lesser) share of information will be found in the underlying market (derivatives market). Ates and Wang (2005) further argue that E-mini index futures make a larger contribution to price discovery during periods of high volatility than during periods of low volatility. Nevertheless, Kawaller, Koch, and Koch (1987) suggest that one of the primary reasons for the existence of informed traders is the leverage effect, whilst trading hours of E-mini futures contracts are virtually 24 hours per day. This study argues that the leverage effect will be significantly higher for informed traders during high-volatility periods. Therefore, a significantly negative relationship between the information share of SPDRs and market volatility is expected

4. EMPIRICAL RESULTS

4.1. Summary Statistics

The changes in the liquidity of SPDRs surrounding the introduction of SPDR options are reported in Table II, which shows that not all of the trading centers experience improvements in terms of the liquidity measures (spread and depth). In the second period, the *MQI* measure, calculated as the ratio between half quoted depth and percentage quoted spread, is enhanced in all four exchanges, which is consistent with Kumar et al. (1998) and de Jong et al. (2006), in that the introduction of options improves the market quality of the underlying securities.

As argued above, higher liquidity indicates a lower market impact cost within the transaction costs as a whole. Accordingly, the study infers that improvements in market liquidity will lead to an increase in the contribution of SPDRs to the overall process of price discovery in the S&P 500 index market.

4.2. Price Discovery Analyses in the SPDR and Futures Markets

4.2.1. Price discovery in the SPDR market

According to the trading cost hypothesis, an asset with lower trading costs will tend to lead in the price-discovery process; this hypothesis implies that a reduction in transaction costs will improve the contribution to price discovery. Based on the literature review provided above, it is evident that following the introduction of SPDR options, there has been an increase in the *MQI* of SPDRs. Therefore, this section examines which trading center plays the most important

TABLE II

Summary Statistics of SPDRs

Trading Centers	*National Best Bid and Offer (NBBO)*								
	No. of Quotes	*%*	*Quoted Depth (×100 Shares)*	*Difference (t-statistic)*	*Quoted Spread*	*Relative Quoted Spread (%)*	*Difference (t-statistic) (%)*	*Market Quality Index (MQI)*	*Difference (t-statistic)*
Panel A: First period (February 25, 2004–January 7, 2005, 220 trading days)									
A (AMEX)	1,478,061	3.03	57.75	–	0.0391	0.0346	–	11.51	–
B (Boston)	123,738	0.25	13.90	–	0.2663	0.2356	–	0.47	–
C (Cincinnati)	7,673,102	15.74	373.45	–	0.0238	0.0210	–	133.12	–
M (Chicago)	298,037	0.61	9.99	–	0.2199	0.1960	–	0.40	–
N (NYSE)	2,174,011	4.46	1038.89	–	0.0365	0.0322	–	168.61	–
P (Pacific)	20,828,224	42.74	386.70	–	0.0149	0.0131	–	139.26	–
T (NASDAQ)	15,923,861	32.67	214.97	–	0.0360	0.0318	–	34.72	–
W (CBOE)	226,422	0.46	495.44	–	0.0590	0.0522	–	61.31	–
X (Philadelphia)	11,539	0.02	22.02	–	0.3286	0.2916	–	0.79	–
Total	48,736,995	100.00	344.79	–	0.0270	0.0239	–	99.98	–
Panel B: Second period (January 10, 2005–November 23, 2005, 220 trading days)									
A (AMEX)	1,805,107	2.50	78.65	20.86***	0.0361	0.0301	−0.0045***	15.69	4.18***
B (Boston)	117,624	0.16	12.37	−1.53***	0.2755	0.2302	−0.0054***	0.46	0.00
C (Cincinnati)	9,053,010	12.55	478.52	105.06***	0.0198	0.0165	−0.0045***	180.92	47.80***
M (Chicago)	1,047,664	1.45	56.15	46.17***	0.1015	0.0841	−0.1119***	6.76	6.36***
N (NYSE)	2,289,504	3.17	383.48	−655.40***	0.0414	0.0345	0.0023***	56.88	–111.73***
P (Pacific)	21,319,619	29.56	628.68	241.96***	0.0173	0.0145	0.0014***	206.02	66.75***
T (NASDAQ)	36,255,265	50.27	166.49	−48.47***	0.0238	0.0198	−0.0119***	41.69	6.97***
W (CBOE)	234,942	0.33	597.12	101.60***	0.0561	0.0470	−0.0052***	81.64	20.33***
Total	72,122,735	100.00	346.52	1.73***	0.0239	0.0199	−0.0040***	107.13	7.15***

Note. The quoted depth (QD) is calculated as ($Q_{bid} + Q_{ask}$) and the quoted spread is calculated as ($P_{ask} - P_{bid}$), where Q_{ask} is the depth at ask, Q_{bid} is the depth at bid, P_{ask} is the ask price and P_{bid} is the bid price. The relative quoted spread (PQS) is calculated as [(P_{ask}–P_{bid})/M], and the *MQI* is calculated as [QD/2/100]/[PQS ×100], where *M* is the midpoint of the bid and ask prices of the quotes. Difference refers to the difference in quoted depth, relative quoted spread and *MQI* between the second and first periods for each SPDR trading center. ***indicates that the difference for the traditional *t*-test is significant at the 1% level.

role in the SPDR price-discovery process both before and after the introduction of SPDR options. Price discovery is modeled in this study using one-second resolution, with lagged terms of up to five minutes, as in Hasbrouck (2003). The trade (quote) price is set as the last sale price (prevailing quote midpoint) at the end of the second period. We also follow the suggestion of Hasbrouck (2003) for the computation of the daily common factor weight, information share and *MIS* measures.

In order to analyze the change in the contribution of SPDRs to price discovery after the introduction of SPDR options, we first examine price discovery of the S&P 500 ETF market on the four venues—AMEX, Island ECN, ArcaEx ECN and NASDAQ. As shown in Table I, these four venues account for 96.52% (97.94%) of all transactions and 92.99% (95.37%) of the total volume in the first (second) period. Therefore, the analysis of the price discovery for SPDRs focuses on these four venues; the remaining exchanges, which account for less than 5% of all transactions, are excluded from the analysis. Although Tse et al. (2006) indicate that ArcaEx accounts for most of the price discovery for SPDRs, duplicating the analysis based on the inclusion of the periods before and after the introduction of SPDR options assists in ensuring the completeness and robustness of this study.

The results of the examination of price discovery in SPDR trades for these four venues are reported in Table III, with Panel A1 showing that the correlation coefficients between the different trading venues are very low, with the exception of the Island and ArcaEx ECNs, where the coefficient is 0.290.

The price-discovery results using the PT, IS and MIS models are reported in Panel A2 of Table III, from which we can see that in the first period, ArcaEx accounts for 56.6% of the price discovery in the PT model, 58.9% in the IS model, and 59.4% in the MIS model, contributions that are much higher than those of any of the other venues. A similar result is also shown in Panel B2 of Table III, again indicating that ArcaEx accounts for most of the price discovery for SPDRs in the second period. These results are consistent with the findings of Tse et al. (2006), that in the price discovery of SPDRs, the ArcaEx ECN dominates all of the other venues.[13] This result also implies that informed traders still favor the ETF electronic trading platform following the introduction of SPDR options trading.

[13]In September 2002, the Island ECN stopped displaying its limit order book in the three most active ETFs where it was the dominant venue. When Island chose to redisplay its quotes about a year later, it was no longer a dominant player. Hendershott and Jones (2005a) indicate that at the same time ArcaEx reduced its fees, improved its technology and discontinued the practice of 'sub-penny' trading, all of which led to improvements in its market share in ETFs, which ultimately resulted in ArcaEx becoming a formidable competitor in the subsequent period. Hendershott and Jones (2005a) and Tse et al. (2006) also show that ArcaEx has proven to be a significant contributor within the overall the process of price discovery.

TABLE III
Analysis of Price Discovery in the SPDR Markets

	AMEX	*Island*	*ArcaEx*	*NASDAQ*
Panel A: First period (February 25, 2004–January 7, 2005, 220 trading days)				
Panel A1: Disturbance correlation matrix				
AMEX	1.000	0.007	0.008	0.003
Island	0.007	1.000	0.290	0.034
ArcaEx	0.008	0.290	1.000	0.045
NASDAQ	0.003	0.034	0.045	1.000
Panel A2: Price-discovery measures				
PT model	0.062	0.322	0.566	0.050
IS model	0.022	0.363	0.589	0.026
MIS model	0.022	0.359	0.594	0.025
Panel B: Second period (January 10, 2005–November 23, 2005, 220 trading days)				
Panel B1: Disturbance correlation matrix				
AMEX	1.000	0.014	0.013	0.004
Island	0.014	1.000	0.276	0.086
ArcaEx	0.013	0.276	1.000	0.157
NASDAQ	0.004	0.086	0.157	1.000
Panel B2: Price-discovery measures				
PT model	0.075	0.298	0.548	0.079
IS model	0.023	0.293	0.607	0.076
MIS model	0.023	0.289	0.615	0.073

Note. The results for trade price discovery using the common factor (PT), information share (IS) and modified information share (MIS) models are reported for the AMEX, Island, ArcaEx and NASDAQ. The statistics are based on a VECM of prices for S&P 500 index securities that are estimated as one-second resolution data. The models are estimated for each day during our sample period (from February 25, 2004 to November 23, 2005, for a total of 440 trading days). The figures throughout the table are the means of the daily estimates. Panels A1 and B1 show the residual correlation matrices of the VECM, whereas Panels A2 and B2 present the daily measures of price discovery.

4.2.2. Price discovery for SPDRs versus futures

The price-discovery results for the SPDR and futures markets using the PT, IS and MIS models are reported in Table IV. We use the SPDR trade prices from the AMEX, Island ECN, ArcaEx ECN and NASDAQ for our analysis of the SPDR market.

The results of the PT model indicate that relative to the other markets, ArcaEx is quite dominant, with a significant contribution to the price-discovery process of 36.5% (37.2%) in the first (second) period. In contrast, the results of the IS and MIS models indicate that E-mini futures are more dominant, contributing approximately 43% (40%) to the price-discovery process in the first (second) period.

Although there are obvious differences in the results obtained from the various models, when comparing the results for the first period with those

TABLE IV

Analysis of Price Discovery in the SPDR and Futures Markets Based on a Comparison Between SPDR and Futures Trades

	AMEX	*Island*	*ArcaEx*	*NASDAQ*	*Regular Futures*	*E-mini Futures*
Panel A: First period (February 25, 2004–January 7, 2005, 220 trading days)						
Panel A1: Disturbance correlation matrix						
AMEX	1.000	0.005	0.004	0.003	0.003	0.002
Island	0.005	1.000	0.263	0.032	0.011	0.099
ArcaEx	0.004	0.263	1.000	0.042	0.014	0.122
NASDAQ	0.003	0.032	0.042	1.000	0.002	0.012
Regular futures	0.003	0.011	0.014	0.002	1.000	0.027
E-mini futures	0.002	0.099	0.122	0.012	0.027	1.000
Panel A2: Price-discovery measures						
PT model	0.060	0.219	0.365	0.048	0.114	0.193
IS model	0.018	0.195	0.293	0.021	0.041	0.432
MIS model	0.018	0.193	0.293	0.021	0.041	0.434
Panel B: Second period (January 10, 2005–November 23, 2005, 220 trading days)						
Panel B1: Disturbance correlation matrix						
AMEX	1.000	0.010	0.008	0.002	0.007	0.006
Island	0.010	1.000	0.249	0.076	0.014	0.092
ArcaEx	0.008	0.249	1.000	0.144	0.014	0.136
NASDAQ	0.002	0.076	0.144	1.000	0.004	0.053
Regular futures	0.007	0.014	0.014	0.004	1.000	0.024
E-mini futures	0.006	0.092	0.136	0.053	0.024	1.000
Panel B2: Price-discovery measures						
PT model	0.071	0.204	0.372	0.061	0.115	0.178
IS model	0.023	0.160	0.332	0.048	0.038	0.400
MIS model	0.023	0.157	0.335	0.046	0.038	0.402

Note. The results of trade price discovery using the common factor (PT), information share (IS) and modified information share (MIS) models are reported for the AMEX, Island, ArcaEx and NASDAQ. The statistics are based on a VECM of prices for S&P 500 index securities that are estimated as one-second resolution data. The models are estimated for each day during our sample period (from February 25, 2004 to November 23, 2005, for a total of 440 trading days). The figures throughout the table are the means of the daily estimates. Panels A1 and B1 show the residual correlation matrices of the VECM, whereas Panels A2 and B2 present the daily measures of price discovery.

for the second period, the contribution made by SPDRs to price discovery within the S&P 500 index market is clearly enhanced by those SPDRs traded on the ArcaEx ECN. This result provides support for the argument that the introduction of SPDR options has helped to improve the contribution made by SPDRs to price discovery as a whole within the S&P 500 index market.

The price-discovery results on the SPDR trade and quote prices in the ArcaEx ECN, the regular futures market and the E-mini futures market are depicted in Table V; these results are provided in order to check the robustness

TABLE V
Analysis of Price Discovery in the SPDR Markets Based on a Comparison Between ArcaEx SPDR Trades and Quotes and Regular and E-mini Futures Prices

	ArcaEx Quote Midpoint	*ArcaEx Trade Price*	*Regular Futures Prices*	*E-mini Futures Prices*
Panel A: First period (February 25, 2004–January 7, 2005, 220 trading days)				
Panel A1: Disturbance correlation matrix				
ArcaEx quote midpoint	1.000	0.322	0.014	0.155
ArcaEx trade price	0.322	1.000	0.008	0.101
Regular futures price	0.014	0.008	1.000	0.023
E-mini futures price	0.155	0.101	0.023	1.000
Panel A2: Price-discovery measures				
PT model	0.560	0.198	0.095	0.147
IS model	0.450	0.170	0.035	0.345
MIS model	0.457	0.161	0.035	0.346
Panel B: Second period (January 10, 2005–November 23, 2005, 220 trading days)				
Panel B1: Disturbance correlation matrix				
ArcaEx quote midpoint	1.000	0.264	0.018	0.127
ArcaEx trade price	0.264	1.000	0.011	0.128
Regular futures price	0.018	0.011	1.000	0.022
E-mini futures price	0.127	0.128	0.022	1.000
Panel B2: Price-discovery measures				
PT model	0.481	0.272	0.097	0.150
IS model	0.333	0.266	0.035	0.366
MIS model	0.335	0.263	0.035	0.368

Note. The results of trade price discovery using the common factor (PT), information share (IS) and modified information share (MIS) models are reported for SPDR trades and quotes on the ArcaEx and compared with regular and E-mini futures prices. The statistics are based on a VECM of prices for S&P 500 index securities that are estimated as one-second resolution data. The models are estimated for each day during our sample period (from February 25, 2004 to November 23, 2005, for a total of 440 trading days). The figures throughout the table are the means of the daily estimates. Panels A1 and B1 show the residual correlation matrices of the VECM, whereas Panels A2 and B2 present the daily measures of price discovery.

of the empirical results and to facilitate a comparative analysis with that of the results obtained by the prior studies (Hasbrouck, 2003; Tse et al., 2006).[14]

First of all, Table V shows that the contribution to price discovery by SPDR trade prices improves significantly in the ArcaEx ECN. This result also provides support for the argument of an increase in the contribution of SPDRs

[14]This study also examines the price-discovery results on the SPDR trade and quote prices in the other three venues (AMEX, Island ECN, and NASDAQ), and find that they are similar to those from the ArcaEx ECN. In addition, the distribution of the contribution to price discovery in the AMEX is also found to be very similar to that reported by Hasbrouck (2003) and Tse et al. (2006). Therefore, these results reemphasize the significant contribution made by SPDRs to price discovery within the S&P 500 index market after the introduction of SPDR options. Consistent with the findings of Huang (2002), the Island and ArcaEx quotes also play an important role in the price-discovery process for SPDRs. In the interests of space, this paper only reports the results pertaining to the ArcaEx ECN.

TABLE VI
Analysis of Price Discovery Based on a Comparison Between AMEX, Island, ArcaEx and NASDAQ SPDR Trades and E-mini Futures Prices

	AMEX vs. E-mini Futures	*Island vs. E-mini Futures*	*ArcaEx vs. E-mini Futures*	*NASDAQ vs. E-mini Futures*
Panel A: First period (February 25, 2004–January 7, 2005, 220 trading days)				
PT model	0.236	0.590	0.689	0.197
IS model	0.047	0.379	0.458	0.048
MIS model	0.047	0.378	0.457	0.048
Panel B: Second period (January 10, 2005–November 23, 2005, 220 trading days)				
PT model	0.282	0.615	0.703	0.321
IS model	0.075	0.386	0.499	0.152
MIS model	0.074	0.386	0.499	0.151

Note. The results of trade price discovery using the common factor (PT), information share (IS) and modified information share (MIS) models are reported for SPDR trades on the AMEX, Island, ArcaEx and NASDAQ and compared with E-mini futures prices. The trade prices are collected at one-second intervals, with the models estimated for each day during our sample period (from February 25, 2004 to November 23, 2005, for a total of 440 trading days). The figures throughout the table are the means of the daily estimates.

to price discovery following the introduction of SPDR options. Furthermore, the results in Panel A of Table V are similar with the results reported in Tse et al. (2006), where an investigation was undertaken into the price discovery in the ArcaEx ECN between May and July 2004.

According to the prior studies (Chu et al., 1999; Hasbrouck, 2003; Tse et al, 2006), S&P 500 index E-mini futures dominate the price-discovery process within the S&P 500 index market. In order to demonstrate the enhanced contribution to price discovery made by SPDRs relative to E-mini futures following the introduction of SPDR options, this study further compares the SPDR trades for each venue (AMEX, Island, ArcaEx and NASDAQ) with the prices of E-mini futures. The results for the PT, IS and MIS models are reported in Table VI.

Firstly, the contribution made to price discovery by SPDRs is found to have improved in all four venues following the introduction of SPDR options. Second, the results on the Island and ArcaEx ECNs from the PT model reveal that the weights of the common factor coefficients are greater than 50%, thereby indicating that as compared with E-mini futures prices, SPDR trades may have become dominant in the overall process of price discovery, particularly with regard to the ArcaEx ECN in the second period. These results reveal that the introduction of SPDR options has enhanced the contribution made by SPDRs to the overall process of price discovery.

TABLE VII
Regression Analyses of Market Liquidity for SPDRs

Variables	*AMEX*	*Island*	*ArcaEx*	*NASDAQ*
D^{Opt}	0.317***	0.299***	0.332***	0.203***
	(4.724)	(7.376)	(7.555)	(2.817)
Log (*Vol*)	0.094	0.099*	0.144***	0.093*
	(1.296)	(1.820)	(2.781)	(1.868)
Volatility	−2.692***	−1.990***	−1.829***	−0.923
	(−3.815)	(−4.890)	(−4.252)	(−1.185)
Constant	1.569**	3.875***	3.432***	2.448***
	(2.073)	(6.129)	(6.071)	(4.518)
Adjusted R^2	0.187	0.400	0.556	0.118

Note. Following the introduction of SPDR options, the changes in the *MQI* are tested based on the following regression model:

$$\log(MQI_t) = \alpha_0 + \alpha_1 D_t^{Opt} + \alpha_2 \log(Vol_t) + \alpha_3 \sigma_t + \varepsilon_t$$

where t denotes the daily time interval, MQI_t refers to the SPDR market quality index during trading day t, D_t^{Opt} is a dummy variable that is equal to 0 for options in the pre-listing period, otherwise 1, Vol_t is the SPDR trading volume during trading day t and σ_t is the Parkinson (1980) extreme value estimator that proxies for the volatility of the S&P 500 index market. The Newey and West (1987) procedure is used to calculate the consistent standard errors of the regression parameter estimates under a serially correlated and heteroskedastic error process. Figures in parentheses are t-statistics. ***indicates the significance of the traditional t-test at the 1% level; **indicates significance at the 5% level and *indicates significance at the 10% level.

4.3. Regression Analyses of Market Liquidity and Price Discovery

Following the introduction of SPDR options, any inferences on improvements in the contribution made to price discovery by SPDRs may well be affected by changes in market liquidity over the sample period. Therefore, we follow Bollen and Whaley (1998) to adopt a dummy variable, along with trading volume and market volatility, all of which are employed as control variables in order to determine the improvements in the market liquidity of SPDRs as a direct result of the introduction of SPDR options.

The regression results are shown in Table VII, which depicts that all of the coefficients on the dummy variable are significantly positive, indicating that the market liquidity of SPDRs is significantly enhanced in all the four venues as a result of the introduction of SPDR options. Furthermore, the impacts on the market liquidity of SPDRs from both trading volume and market volatility are found to be consistent with the arguments of Bollen and Whaley (1998), in that greater price variability or a lower trading volume results in a lower *MQI*.

This study infers that improvements in the contribution made by SPDRs to price discovery are caused by the increase in market liquidity as a direct result of the introduction of SPDR options. Details on the relationship that exists between price discovery and the *MQI* based on the regression analysis are presented in Table VIII. The results of Model (1) in Table VIII-based upon Equation (10)–reveal that the coefficients on D_t^{Opt} are all positive, thereby indicating a clear increase in the contribution made to price discovery by SPDRs as a result of the introduction of SPDR options.

Relative to all the other trading venues, the ArcaEx ECN is found to be dominant in the price-discovery process, since the results show that the coefficient on the dummy variable is significantly positive for ArcaEx, thereby implying that the contribution made by SPDRs to price discovery increases as a result of the introduction of SPDR options.

In order to provide support for the argument that this improvement in the contribution of the SPDRs to price discovery is caused by enhancements to market liquidity, the *MQI* is inserted into Equation (10) to obtain Equation (11). Model (2) in Table VIII shows that the coefficients on the *MQI* variable reveal significant explanatory power offsetting the effect of the dummy variable on the price discovery measures, especially for the ArcaEx ECN. In addition, the new regression models, with the addition of the *MQI* variable, almost always present insignificant constant terms and higher adjusted R^2 values than the original regression models. The results listed in Tables VII and VIII clearly demonstrate that the introduction of SPDR options results in improved liquidity within the SPDR market, which in turn leads to a substantial rise in the contribution made by SPDRs to the overall process of price discovery. As Bloomfield et al. (2005) point out, results such as these also raise the possibility that informed traders provide more liquidity after the introduction of SPDR options.

The coefficients on the volatility variable are found to be negative, and nearly attain significance in Table VIII, a finding which indicates that informed traders have a preference for trading on the E-mini futures market during periods of high volatility. These results can be seen as providing support for the leverage hypothesis proposed by Kawaller et al. (1987) where during periods of high volatility, informed traders have a preference for using high leverage instruments.

An additional advantage of E-mini futures—the fact that these instruments can be traded on an almost 24-hour basis—may also represent a strong attraction for informed traders to trade in the E-mini futures market during periods of high volatility, since this feature offers them the ability to adjust their position at any time. In contrast with Chakravarty et al. (2004), this finding stresses the importance of the leverage hypothesis on the analysis of price discovery in high-volatility periods.

TABLE VIII

Regression Analyses of Price Discovery for SPDRs

	AMEX		Island		ArcaEx		NASDAQ	
Variables	*Model (1)*	*Model (2)*	*Model (1)*	*Model (2)*	*Model (1)*	*Model (2)*	*Model (1)*	*Model (2)*
Panel A: Common factor (PT) model								
D^{Opt}	0.042**	0.029	0.017	−0.014	0.009	−0.046*	0.116***	0.109***
	(2.306)	(1.360)	(0.958)	(−0.571)	(0.638)	(−1.736)	(6.304)	(5.502)
Log (Vol_t/Vol_{t-1})	0.076**	0.064**	0.046**	0.040**	0.058***	0.041**	0.018	0.017
	(2.478)	(2.058)	(2.544)	(2.334)	(3.196)	(2.036)	(1.092)	(1.019)
Volatility	−0.525**	−0.383	−1.438***	−1.270***	−0.951***	−0.731***	−1.368***	−1.356***
	(−2.022)	(−1.391)	(−5.463)	(−4.747)	(−3.959)	(−2.784)	(−6.376)	(−6.368)
Log (*MQI*)	–	0.044	–	0.095*	–	0.140**	–	0.027
	–	(1.295)	–	(1.928)	–	(2.286)	–	(1.243)
Constant	0.283***	0.167*	0.717***	0.239	0.773***	0.066	0.318***	0.226***
	(10.531)	(1.810)	(28.876)	(0.975)	(35.222)	(0.212)	(13.236)	(2.995)
Adjusted R^2	0.033	0.037	0.082	0.110	0.042	0.075	0.196	0.200
Panel B: Information share (IS) model								
D^{Opt}	0.026***	0.022**	0.001	−0.024	0.036*	−0.035	0.101***	0.099***
	(2.639)	(2.148)	(0.034)	(− 0.753)	(1.696)	(− 0.888)	(7.975)	(7.437)
Log (Vol_t/Vol_{t-1})	0.047**	0.044**	0.068***	0.063***	0.101***	0.079**	0.019	0.019
	(2.407)	(2.174)	(2.772)	(2.668)	(3.174)	(2.309)	(1.442)	(1.410)
Volatility	−0.242**	−0.201*	−1.059***	−0.924***	−0.917***	−0.632*	−0.465***	−0.462***
	(−2.178)	(−1.814)	(− 3.467)	(− 2.877)	(− 2.621)	(− 1.692)	(−3.120)	(−3.068)
Log (*MQI*)	–	0.013	–	0.076	–	0.181**	–	0.006
	–	(0.794)	–	(1.239)	–	(2.078)	–	(0.400)
Constant	0.069***	0.035	0.473***	0.090	0.539***	−0.376	0.089***	0.069
	(5.814)	(0.825)	(14.947)	(0.291)	(15.681)	(− 0.854)	(5.932)	(1.278)
Adjusted R^2	0.036	0.036	0.028	0.042	0.027	0.047	0.194	0.193

(*Continued*)

TABLE VIII *(Continued)*

	AMEX		Island		ArcaEx		NASDAQ	
Panel C: Modified information share (MIS) model								
D^{Opt}	0.026***	0.022**	0.001	−0.024	0.036*	−0.035	0.100***	0.099***
	(2.633)	(2.143)	(0.039)	(− 0.751)	(1.697)	(− 0.885)	(7.931)	(7.397)
Log (Vol_t/Vol_{t-1})	0.047**	0.044**	0.068***	0.063***	0.102***	0.080**	0.019	0.019
	(2.407)	(2.174)	(2.762)	(2.657)	(3.176)	(2.313)	(1.438)	(1.407)
Volatility	−0.242**	−0.200*	−1.067***	−0.931***	−0.929***	−0.642*	−0.464***	−0.462***
	(−2.177)	(−1.813)	(−3.473)	(− 2.882)	(−2.629)	(−1.702)	(−3.115)	(−3.063)
Log (MQI)	–	0.013	–	0.077	–	0.182**	–	0.006
	–	(0.793)	–	(1.241)	–	(2.075)	–	(0.393)
Constant	0.069***	0.035	0.473***	0.087	0.540***	−0.382	0.089***	0.070
	(5.810)	(0.825)	(14.856)	(0.280)	(15.553)	(− 0.860)	(5.922)	(1.281)
Adjusted R^2	0.036	0.036	0.028	0.042	0.027	0.047	0.192	0.191

Note: Following the introduction of SPDR options, the changes in the contribution of SPDRs to price discovery are tested based on the following regression model (Equation 10):

$$PD_t = \beta_0 + \beta_1 D_t^{Opt} + \beta_2 \log(Vol_t y\ Vol_{t-1}) + \beta_3 \sigma_t + \varepsilon_t \qquad \text{(Model 1)}$$

where t indicates the daily time interval, PD_t refers to the daily share of information for SPDRs measured by the common factor (PT), information share (IS) and modified information share (MIS) models for SPDR trades on an venue and compared with E-mini futures prices, D_t^{Opt} is a dummy variable that is equal to 0 for options in the pre-listing period, otherwise 1; Log(Vol_t/Vol_{t-1}) is the rate of change in trading volume for SPDRs during trading day t and σ_t is the Parkinson (1980) extreme value estimator that proxies for the volatility of the S&P 500 index market. In order to provide support for our argument that the improvement in the contribution of SPDRs to price discovery is caused by enhancements to market quality, the MQI is added into the above equation and defined as follows (Equation 11):

$$PD_t = \beta_0 + \beta_1 D_t^{Opt} + \beta_2 \log(Vol_t y Vol_{t-1}) + \beta_3 \sigma_t + \beta_4 \log(MQI_t) + \varepsilon_t \quad \text{(Model 2)}$$

where MQI_t refers to the SPDR market quality index during trading day t. Model (2) is estimated by using the two-stage least-squares (2SLS) approach, which uses the lagged *MQI*, lagged market volatility and the previous day's trading volume as the instrument variables for the *MQI*. The Newey and West (1987) procedure is used to calculate the consistent standard errors of the regression parameter estimates under a serially correlated and heteroskedastic error process. Figures in parentheses are *t*-statistics. ***indicates the significance of the traditional *t*-test at the 1% level; **indicates significance at the 5% level and *indicates significance at the 10% level.

5. CONCLUSIONS

This study examines the impact of the introduction of SPDR options on the contribution to price discovery made by SPDRs. Consistent with the findings of Kumar et al. (1998) and Chakravarty et al. (2004), we find that the introduction of SPDR options has improved the liquidity of SPDRs, which has further reduced their implicit trading costs. According to the 'transaction cost' hypothesis of Fleming et al. (1996), those securities with lower trading costs make a higher contribution to price discovery. We therefore argue that following the introduction of SPDR options, the major benefit for market participants from the improvement in market liquidity has led to a reduction in the implicit trading costs, which in turn, may have induced a greater contribution to price discovery by SPDRs.

Furthermore, when comparing only the contributions to price discovery made by SPDRs and E-mini futures, the SPDRs traded on ArcaEx are found to make a contribution of about 50% to the price-discovery process. The empirical results also indicate that informed traders have a preference for trading on the E-mini futures market during periods of high volatility, thereby highlighting the importance of the leverage hypothesis for the analysis of price discovery in high-volatility periods. Overall, these findings imply that developments in the derivatives markets can lead to improvements in market quality for the underlying securities in terms of both liquidity and price discovery.

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