The Effect of Institutional Ownership on Price Discovery

Wei-Peng Chen, Huimin Chung, and Donald Lien *

ABSTRACT

This study investigates the relationship between price discovery and institutional ownership using data from S&P 500 index and its derivative products: the index futures, the index options, the S&P 500 exchange-traded funds (SPDRs), and the SPDR options. Empirical results reveal that the contribution of SPDRs to price discovery has exceeded the contribution of E-mini index futures due to increasing institutional ownership in SPDRs. Moreover, SPDRs traded on NASDAQ dominate the price-discovery process in the SPDR market. Nonetheless, in the high volatility period only, E-mini index futures contribute higher information share than SPDRs; hence E-mini index futures play an important role on hedge strategies. Overall, the rapid growth of algorithmic trading (AT) and high-frequency trading (HFT) used by institutional investors are important factors to the price-discovery process.

Keywords: S&P 500 index and derivative markets, Price discovery, Institutional ownership, Algorithmic trading, High-frequency trading

JEL Classification: G13, G20, C32

* Wei-Peng Chen is at the Department of Information and Finance Management at National Taipei University of Technology, Taipei, Taiwan; Huimin Chung is at the Graduate Institute of Finance at the National Chiao Tung University, Hsinchu, Taiwan; Donald Lien is at the Department of Finance, University of Texas at San Antonio, San Antonio, Texas, USA and Graduate Institute of Economics, Tsinghua University, Beijing, China.

1. INTRODUCTION

In this study we examine whether Standard and Poor's Depository Receipts Trust Series I (SPDRs) provide more contribution to price discovery and play a dominant role in the price-discovery process resulting from the increased pattern in institutional holding and trading over the past few years. To proceed, we analyze the dynamics of price discovery between the S&P 500 index and its four most active index products and derivatives: E-mini index futures, index options, SPDRs, and SPDR options. The lead-lag relationship and price discovery function in informationally linked markets, such as futures, options and spot markets, have been analyzed in numerous studies;[1] however, there is no study within the literature discussing these issues that more than three assets and relating to ETF options. We therefore set out in this study to examine the process of price discovery amongst these derivatives, discussing the applications of various price-discovery hypotheses and evaluating whether the existence of the associated derivatives helps promote the completeness and efficiency of the overall market. Based upon these results, this study further explores the link between price discovery and institutional ownership in the SPDR markets, providing possible factors to explain the changes in price discovery of SPDRs. Especially, Chordia, Roll, and Subrahmanyam (2011) and Angel, Harris, and Spatt (2011) indicate the important trends that increases in institutional trading activity and reduction in trading costs in the U.S. equity markets.

In addition to the importance of market completeness, developments in the derivatives market can also lead to improvements in market quality, including liquidity and price discovery of the underlying securities. This study investigates the price discovery among the S&P 500 index markets, noting that derivatives markets

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[1] Examples of studies discussing the process of price discovery between linked markets include: Kawaller et al. (1987), Stoll and Whaley (1990), Chan (1992), Fleming et al. (1996), Booth et al. (1999), Chu et al. (1999), Hentze and Seiler (2000), and So and Tse (2004).

are more likely to incorporate information more efficiently than their underlying asset markets, essentially because of their inherent low transaction costs and greater leverage, as well as the absence of short-sales restrictions. Although prior studies argued that the E-mini index futures denominate the price-discovery process, a finding that ETFs play a significant role in the price-discovery process is also proven.[2] According to the leverage hypothesis on price-discovery analysis, this empirical result provides another motivation to evaluate whether SPDR options offer a greater contribution to price discovery than SPDRs or E-mini index futures. By examining the market prices of the S&P 500 spot index, the S&P 500 index E-mini futures prices, the SPDRs prices, the synthetic prices from the S&P 500 index option, and the synthetic prices from the SPDR options, this study discovers which product plays the most important role in the mechanism of price discovery in the S&P 500 index market.

The evidence that ETFs play a significant role in the price-discovery process was documented in Tse et al. (2006) and Chen and Chung (2012). Following the previous literature, there are three possible explanations as to why SPDRs' contribution to price discovery may have exceed that of E-min S&P 500 index futures, although many studies suggested that E-mini futures contribute the most to price discovery. First, demands of international investors for SPDRs have increased substantially over the past few years, and there is a significant increasing pattern revealed on institutional ownership of SPDRs. For example, Chu et al. (1999) indicate that institutional traders are block investors holding broad-based portfolios, and they usually are endowed with superior market-wide information. Most of institutional traders are restricted by regulation from trading on derivatives market, and they may favor the index securities

[2] Chen and Chung (2012) show that the contribution of SPDRs to price discovery has become very close to that of E-mini index futures after the introduction of SPDR options.

such as ETFs. In addition, French (2008) indicate that institutions shift a large portion of their U.S. equity holdings from active to passive investment over time. Boehmer and Kelley (2009) show that assets with greater institutional ownership are priced more efficiently. The information efficiency effect results from an increase in competition among institutional investors. Competition promotes the rate at which private information is incorporated into prices, improving the contribution to price discovery.

Second, AT and HFT activities grow rapidly in the SPDR market after 2005.[3] Prior studies argue that both AT and HFT contribute to the discovery of efficient price (Hendershott & Riordan, 2013; Brogaard, Hendershott & Riordan, 2014). Brownlees, Cipollini and Gallo (2011) indicate that AT consists of automated trading strategies that attempt to minimize transaction costs by optimally placing orders. Both AT and HFT can improve the mechanism of price discovery because such trading enable market participants to drastically speed up the reception of market data, internal calculation procedures, order submission and reception of execution confirmations. AT and HFT are also associated with institutional trading activities. For example, Chordia et al. (2011) mention that a technological factor leading to an increase in institutional turnover is likely the increasing prevalence of AT by hedge funds and other institutions. Furthermore, the introduction of ETF options provides investors with an opportunity to execute AT or/and HFT strategies using combinations of ETFs and ETF options. In addition, development in dark pools can offset the effect of decline in depth, assist informed traders using AT and HFT (Hendershott et al., 2011), and facilitate the price-discovery process.

Third, the sustained improvement in SPDRs' liquidity is helpful to enhance the

[3] Owing to developments like decimalization and advances in information technology, high-frequency traders operate in massive scales. Hendershott et al. (2011) indicate that many institutional investors trade via algorithms and markets have become more liquid, especially in the 5 years following decimalization.

mechanism of price discovery.[4] Chordia et al. (2011) show the recent trends that bid-ask spreads and trading costs have declined substantially in the period 1993-2008. This improvement in SPDRs' liquidity may be caused by many factors such as the demand of institutional investors (Agarwal, 2007), AT and HFT activity (Hendershott et al., 2011), and development of off-exchange trading (O'Hara & Ye, 2011), etc. The research report provided by Goldman Sachs tallied up the costs associated with E-mini futures and ETFs, estimating that the market impact cost is the same for both E-mini futures and SPDRs.[5] Chakravarty, Panchapagesan, and Wood (2005) and French (2008) show that institutional commissions have declined over time, thereby contributing to improve price discovery by the increasing institutional ownership. Furthermore, Chordia et al. (2011) indicate that dramatic improvements in technology have allowed computer algorithms to speedily discern profit opportunities and determine optimal order submission strategies, typically by dividing up a large order into smaller trades to reduce market impact. According to the transaction cost hypothesis, the sustained improvement in SPDRs' liquidity, which is equal to a reduction in implicit trading cost (market impact cost), will further enhance the mechanism of price discovery.

The empirical results reveal that the SPDR dominates the price-discovery process in the S&P 500 index markets, but E-mini index futures provide most contribution to price discovery in the high volatility period, emphasizing the importance of the hedge function in E-mini index futures. This is the first study that shows price discovery mostly occurs in the SPDR market. We also find that the SPDR prices traded on NASDAQ dominates all other venues after NASDAQ became operational as an exchange for other exchange-listed securities on February 12, 2007.

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[4] According to the study of Chen and Chung (2012), the market quality index, which is defined as the ratio of the quoted depth to the percentage quoted spread, is estimated about 99.98 in 2004 and 107.13 in 2005. In this study, Table 2 presents that the market quality index is estimated about 172.95 in 2006 and 183.17 in 2007. This result shows the evidence that liquidity has improved in the SPDR market.

[5] The Appendix Table A1 illustrates the detail comparison in transaction costs of E-min S&P 500 index futures versus SPDRs.

From the changes in trading activity (e.g., increases in trading volume and number of trades and decreases in average trade size) in the SPDR market, we infer that the growth of AT and HFT activities is obviously occurring in the SPDR market. The regression results demonstrate that increases in the institutional ownership of SPDRs and the growth of AT and HFT activity in the SPDR market are related to the improvement in the contribution of SPDRs to price discovery.

In addition, this study shows that the index derivatives with leverage characteristic, such as regular and E-mini futures, index options, and ETF options, have more contributions to price discovery in high volatility period than in normal volatility period. This finding strengthens the importance of the leverage hypothesis in the price-discovery analysis during high volatility periods. Overall, this study shows that SPDRs dominate the price-discovery process in the normal period and E-mini index futures dominate the price-discovery process in the high volatility period.

The remainder of this paper is organized as follows. A review of the related literature is provided in Section 2, followed in Section 3 by a discussion of the data and research methodology. Section 4 presents the empirical results on the price-discovery analysis. Finally, conclusions drawn from this study are presented in Section 5.

2. LITERATURE REVIW

The recent trends in trading activity, which include decreased trading costs and increased share turnover, have been proven to affect market efficiency significantly. Chordia, Roll, and Subrahmanyam (2011) explore these trends in financial markets and indicate institutional holdings and trading, which is a widespread use of quantitative trading strategies, play a dominant role in these trends.[6] The uptrend in institutional trading is associated with an important development in the growth of new information processing and communications technologies; therefore, it has become easier for institutions to execute automated algorithmic trading (Hendershott, Jones, & Menkveld, 2011) and for exchanges to accommodate large trading volumes (Chordia et al., 2011). Furthermore, Angel, Harris, and Spatt (2011) point out that increasing automation and the entry of new trading platforms have resulted in intense competition among trading platforms. The development in the information technology has led to increases in institutional trading activity and reduction in trading costs in the U.S. equity markets.

About the influences of institutional holding and trading in market quality, Boehmer and Kelly (2009) show that price efficiency is directly related to institutional holdings, suggesting that the presence of institutional investors improves the information environment of a firm.[7] For the U.S. equity securities, 'exchange-traded funds' (ETFs) are the proxies for most major stock market indices, and hence particularly attractive to institutional investors. French (2008) argues institutional costs decline over time because the costs for active and passive investments decline and the institutions shift a large portion of their U.S. equity holdings from active to passive investments. Accordingly, the ETF, as a typical passive investment instrument, has higher institutional ownership than other equity securities with a significant uptrend pattern over the past few years.[8] Motivated by the increased patterns in institutional holding and trading of ETFs, we address an important question on the price discovery

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[6] Chordia et al. (2011) indicate the link between increased trading by institutions and price formation. They argue that institutions are able to trade more effectively on private information and finding about return predictability, thereby contributing to increased market efficiency.

[7] Boehmer and Kelly (2009) summarize prior studies (Holden & Subrahmanyam, 1992; Brennan & Subrahmanyam, 1995; Nagel, 2005; Boehmer, Jones, & Zhang, 2008; Boehmer & Wu, 2013) and offer a number of potential explanations.

[8] For example, until the end of June 2014, the institutional ownership of SPDRs has up to about 80%.

analysis: Does the contribution of ETFs exceed that of E-mini index futures in the price-discovery process?

The ETF is an index product and represents a basket of securities. Standard and Poor's Depository Receipts Trust Series I (SPDRs) which track the Standard and Poor's (S&P) 500 index were first listed on the American Stock Exchange (AMEX) on 29 January 1993, and have since become the most active ETFs.[9] The S&P 500 index is a very important indicator in the global financial markets. Based upon the S&P 500 index, the main popular derivatives comprise of index futures, index options, ETFs, and options on ETF. When a single financial asset or multiple highly related financial assets such as its derivatives are traded on more than one market, each product or market may contribute to the price-discovery process. Which derivative product dominates the price-discovery process in the S&P 500 index market? This issue is important not only for the U.S. investors but also for global market participants since global financial markets have become increasingly integrated.

As noted in O'Hara (2003), two of the most important functions of the financial markets are price discovery and liquidity provision. In complete and efficient markets, financial asset prices reflect the information available to market participants; otherwise, there would be possibilities of costless arbitrage profits. Price discovery is a process by which markets incorporate this information to arrive at equilibrium financial asset prices. In practice, however, differences in information transmission between products or markets are brought about both by the existence of frictions within the market and the differences in trading costs across different market structures. Thus, a market which is capable of adjusting prices more rapidly will undoubtedly demonstrate superior ability in the overall process of price discovery, a process which is concerned

[9] On January 17, 2008, NYSE Euronext announced it would acquire the AMEX for $260 million in stock; on October 1, 2008, NYSE Euronext completed the acquisition.

mainly with how rapidly market prices react to new information, and how such information is used. Price discovery is therefore a process which essentially focuses on the analysis of market efficiency.

The price-discovery process is influenced by many market characteristics. Theoretical analyses suggest that markets with greater liquidity, lower transaction costs, and fewer restrictions are likely to play more important roles in terms of price discovery.[10] Even for the same product, different market microstructure designs, such as trading environment and platforms, affect the transactions of informed traders to reflect information on the price-discovery process (Tse et al., 2006; Simaan & Wu, 2007; Chen & Chung, 2012). In addition, the development trend of moving stocks and derivatives trading from exchange trading floors to electronic communications networks (ECNs), together with the technology progress and development, allow new electronic trading platforms to offer low-cost and high-speed market access.[11] These electronic systems provide a wholesome environment for algorithmic trading (AT) and high-frequency trading (HFT) and subsequently the influence of AT and HFT on market quality become a prominent issue in financial markets. Furthermore, dark pools and other off exchange trading allow informed agents to trade strategically on both dark and lit venues and facilitate the price discovery process (Hendershott et al., 2011; Zhu, 2012; Nimalendran & Ray, 2014).[12] Overall, these market and trading revolutions in the SPDR market raise a question regarding the possible dominating role of the SPDR in

[10] 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. Chakravarty et al. (2004) show that price discovery is related to trading volume, spreads, and volatility.

[11] Markham and Harty (2008) provide a detail description for the background and developments of ECNs.

[12] Hendershott et al. (2011) argue that some dark pools allow traders with large orders to electronically search for counterparties without revealing their trading interest and can offset the decline in depth contributed by AT. O'Hara and Ye (2011) investigate that dark pools contribute to increased market fragmentation and find no harm to market quality. Zhu (2012) and Nimalendran and Ray (2014) suggest that dark venues facilitate the price-discovery process.

the price-discovery process on the S&P 500 index market.

3. DATA AND RESEARCH METHODOLOGY

3.1 Data Description

The sample of this study includes the S&P 500 index, the S&P 500 index regular futures, the S&P 500 index E-mini futures[13], the S&P 500 index options, SPDRs, and SPDR options. 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.

On February 12, 2007, NASDAQ became operational as an exchange in non-NASDAQ listed securities; NASD and NASDAQ act as separate entities in the Consolidated Tape Association (CTA) plan.[14] NASDAQ began to send its best bid and offer quotation and trade data to SIAC under the Market Center ID of “T”. NASD “D” market center quote on Consolidated Quote System (CQS) reflect NASD ADF participant data only. In order to maintain the consistency of exchanges on our data, the research period is set to from February 12, 2007. Therefore, the sample of this study covers the period from 12 February 2007 to 31 October 2007.

13 The prior studies (Hasbrouck, 2003; Kurov & Lasser, 2004; Ates & Wang, 2005; Tse et al. 2006; Chen & Chung, 2012) show that the E-mini index futures significant lead the regular index futures in the price-discovery process. This study also examines the contributions of E-mini and regular index futures to price discovery and finds that the contribution made by E-mini index futures is far greater than that provided by regular index futures. In the price-discovery analysis between E-mini and regular index futures, E-mini index futures account for 73.94%, 95.14%, and 96.16% of price discovery in PT, IS, and MIS models, respectively. Therefore, we only use the E-mini index futures in the comparisons of the price-discovery analysis.

14 As note in Financial Industry Regulatory Authority (FINRA) website (http://www.finra.org/Industry/Regulation/Guidance/NationalMarketSystemPlans/), the CTA/CQ Plans governs the collection, processing, and distribution of quotation and transaction information for exchange-listed securities (excluding those securities listd on the Nasdaq Stock Exchange). The data reflected on the consolidated tape (Networks A and B) is derived from various market centers, including securities exchanges, FINRA, electronic communications networks (ECNs), and other broker-dealers. Under the CTA/CQ Plans, all U.S. exchanges and associations that quote and trade exchange-listed securities must provide their data to a centralized securities information processor (SIP) for data consolidation and dissemination.

The tick-by-tick data on the S&P 500 index, S&P 500 index E-mini futures, S&P 500 index options, and SPDR options are obtained from the Tick Data database, while the SPDRs data, which includes the tick-by-tick trade prices and trading volume are obtained from the NYSE Trade and Quote (TAQ) database. This study retains only those trades that occurred during regular trading hours between 9:30 a.m. and 4:00 p.m., EST. The corresponding data on the S&P 500 index, regular and E-mini index futures, index options, and SPDR options are obtained from the Tick Data intraday database. In addition, the SPDRs dividend data are obtained from the University of Chicago's Center for Research in Security Prices database (CRSP) and the three-month T-Bill rates on the secondary market, obtained from the web-based Federal Reserve Board database, are used as the risk-free rate (as a proxy for the opportunity costs of arbitrage trades). Finally, the institutional ownership of SPDRs, which is calculated as the institutional shares held divided by shares outstanding, is obtained from the quarterly 13-f reports in the Thomson/CDA Spectrum database.

In order to ensure the accuracy of the sample data, all trades and quotes that are out of time sequence are deleted.[15] Data errors are further minimized by eliminating trades and quotes meeting the criteria outlined in prior studies (Hasbrouck, 2003; Tse et al., 2006; Chen & Chung, 2012). 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., $\left|(P_t - P_{t-1})/P_{t-1}\right| > 0.1$.

3.2 Put-Call Parity and Implied Spot Prices

[15] 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.

The market for S&P 500 index options has grown very quickly since they are introduced at the CBOE on July 1st 1983. Although index options are usually traded on multiple exchanges such as the AMEX, the Philadelphia Stock Exchange (PHLX), the Pacific Stock Exchange (PCX), the Chicago Stock Exchange (CHX), the NYSE, and the International Securities Exchange (ISE), the S&P 500 index options are solely licensed to the CBOE. On January 10th 2005, several U.S. exchanges, which include the AMEX, the Boston Options Exchange (BOX), the CBOE, the ISE, and the PHLX, began trading options on SPDRs. Comparing SPDR options with the S&P 500 index options in their product specifications, the main difference within the both options is exercise style. Index options are European; however, the ETF options are American.

This study applies the put-call parity approach to the calculation of the implied spot prices in order to avoid the modeling estimation biases resulting from the direct calculation of the implied spot prices based upon the Black-Scholes equation. This method, as proposed by Hsieh et al. (2008), has the advantages of mitigating the inherent model risk of the conventional methodologies, whilst avoiding the estimation of unknown volatility in the recovery of the option-implicit spot prices. 'Put-call parity' (PCP) refers to the relationship existing between the price of a call option and the price of a put option on a spot asset according to a standard model; this is dependent upon the assumptions of high efficiency and no-arbitrage opportunities within the market. This approach shows that the value of a European call with a certain strike price and exercise date can be deduced from the value of a European put with the same strike price and exercise date. The PCP equation for implied spot index of the S&P 500 index options is:

$$\hat{S}_0 = C - P + Xe^{-rT}\,, \tag{1}$$

where C is the value of the call at time t; P is the value of the put; S_0 is the spot price at time 0; T is the expiration date of the index option; r is the continuously compounded risk-free interest rate for an investment maturing at time T;[16] and X is the strike price. The PCP input factors can therefore be obtained from the market trading information or the contract specification; thus, whilst offering the benefits of reducing model risk as well as the burden of volatility estimation, the PCP approach also requires no volatility input.

It is, however, important to note that SPDR options are American options which have the possibility of early exercise. A modified put-call parity equation for use with American options is applied in this study, as follows:

$$S_0 - D - X \le C - P \le S_0 - Xe^{-rT} \tag{2}$$

where C is the value of the call; P is the value of the put; S_0 is the current spot price; T is the expiration date of the option; r is the continuously compounded risk-free interest rate for an investment maturing at time T; X is the exercise price of the option; and D is the present value of the dividends during the life of the option.[17]

As noted above, the input factors can be obtained from the market trading information or the contract specification of the option. The upper and lower bounds for the implied spot price then become:

$$\begin{cases} \hat{S}_{0,lower} \ge C - P + Xe^{-rT} \\ \hat{S}_{0,upper} \le C - P + D + X \end{cases} \tag{3}$$

The implied spot price of the option ($\hat{S}_0$) can be calculated using the average of the upper and lower bounds. Next, according to the weighted average method of constructing volatility index (VIX) by CBOE, we select two contracts ($X_u \ge S_0$, $X_l < S_0$)

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[16] The risk-free rate is obtained from the Option Metrics database.

[17] The SPDRs dividend data are obtained from the University of Chicago's Center for Research in Security Prices database (CRSP). A dividend is assumed to occur at the time of its ex-dividend date.

which are closest to at-the-money in the separate near and second-near contracts.[18] Thus, we can obtain the four separate implied spot prices, which are listed as follows: (i) $\hat{S}_1^{X_l}$ is the implied spot price of the nearby contract with strike price X_l; (ii) $\hat{S}_1^{X_u}$ is the implied spot price of the nearby contract with strike price X_u; (iii) $\hat{S}_2^{X_l}$ is the implied spot price of the second-nearby contract with strike price X_l; (iv) $\hat{S}_2^{X_u}$ is the implied spot price of the second-nearby contract with strike price X_u.

Using Equation (4) to calculate the nearest at-the-money implied spot prices of the two nearest-term contracts ($\hat{S}_1$, $\hat{S}_2$), we can then go on to interpolate $\hat{S}_1$ and $\hat{S}_2$ in order to generate the single value, $\hat{S}_0$, with a maturity of N ($N_{t1} \le N \le N_{t2}$) days to expiration, using Equation (5).

$$\hat{S}_i = \hat{S}_i^{X_l}\left(\frac{X_u - S_0}{X_u - X_l}\right) + \hat{S}_i^{X_u}\left(\frac{S_0 - X_l}{X_u - X_l}\right), \quad i = 1 \text{ and } 2. \tag{4}$$

$$\hat{S}_0 = \hat{S}_1\left(\frac{N_{t2} - N}{N_{t2} - N_{t1}}\right) + \hat{S}_2\left(\frac{N - N_{t1}}{N_{t2} - N_{t1}}\right) \tag{5}$$

where N_{t1} is the number of days to expiration of the nearby options; and N_{t2} is the number of days to expiration of the second-nearby options. Therefore, we derive the implied S&P 500 index and the implied SPDR price from the S&P 500 index options and the SPDR options respectively to examine the dynamics of price discovery in the S&P 500 index markets.

Simaan and Wu (2007) analyze how the different microstructure designs affect the price discovery of options quotes and how they alter the flow of options trading

[18] The nearest and second-nearest contracts are used in the calculation of the implied spot prices; since these are the most actively traded, their prices contain more information. However, where there are eight days left to expiration, the two nearest-term contracts are rolled over to the second and third contract months in order to minimize pricing anomalies that might occur close to expiration.

activities over time. Their analysis shows that among the five options exchanges (i.e., the AMEX, CBOE, ISE, PCX, and PHLX), quotes from the ISE have the highest average information share and the CBOE have second highest average information share. Therefore, in this study the price-discovery analysis on SPDR options is examined by using the tick-by-tick data from the ISE and CBOE. According to the information share of SPDR options among the two exchanges, the result of this study also shows that, on average, the ISE has the higher information share estimate than the CBOE.[19]

3.3 Measurement of Price Discovery

For one security trading in multiple venues or multiple highly related financial derivatives based on the same underlying asset, 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 to investigate the mechanics of price discovery: the 'permanent-transitory' (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 relationships and differences between PT and IS models have been discussed at length in the literature. The Gonzalo and Granger (1995) model focuses on the common factor components and the process of error correction, whereas the Hasbrouck

[19] From the price discovery analysis of SPDR options between the ISE and CBOE, in the first (second) period the synthetic prices from the SPDR options in ISE account for 50.72% (51.34%), 53.42% (51.75%), and 53.60% (51.96%) of price discovery in PT, IS, and MIS models respectively. From the result that the information shares contributed by the ISE are all more than 50%, we therefore only use the synthetic prices from the SPDR options in the ISE in the price-discovery analysis.

(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 et al. (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 et al., 1999; Chu et al., 1999; Hasbrouck, 2003; So & Tse, 2004; Chen & Chung, 2012). The analysis begins with the estimation of the VECM. According to Engle and Granger (1987), the representation of the VECM can be shown as follows:

$$\Delta Y_t = \mu + \Pi Y_{t-1} + \sum_{i=1}^{k} A_i \Delta Y_{t-i} + \varepsilon_t \tag{6}$$

where $\Pi Y_{t-1} = \alpha\beta^T Y_{t-1} = \alpha z_{t-1}$; Y_t is an $n \times 1$ vector of cointegrated prices; A_i represents an $n \times n$ matrix of autoregressive coefficients; k is the number of lags; $z_{t-1} = \beta^T Y_{t-1}$ 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 vector α of the error correction term measures the price reaction to the deviation from the long-run equilibrium relationship. The current study follows Hasbrouck (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:

$$z_t = \left[(Y_{1t} - Y_{2t}) \quad (Y_{1t} - Y_{3t}) \quad \cdots \quad (Y_{1t} - Y_{nt}) \right]^T . \tag{7}$$

3.3.1 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 permanent-transitory (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:

$$Y_t = f_t + G_t \tag{8}$$

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 $f_t = \Gamma^T Y_t = (\alpha^T{}_\perp \beta_\perp)^{-1} \alpha^T{}_\perp Y_t$, where Γ is the common factor coefficient vector, Γ is normalized so that the sum its components 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 $\beta_\perp$.

3.3.2 Measurement of information share (IS)

Hasbrouck (1995) defines price discovery as the variance of the innovations to the common factor. The information share (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 (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:

$$\Delta Y_t = \psi(L)\varepsilon_t, \tag{9}$$

along with its integrated form:

$$Y_t = Y_0 + \psi(1)\sum_{i=1}^{t}\varepsilon_i + \psi^*(L)\varepsilon_t, \tag{10}$$

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}. $\psi(L)$ and $\psi^*(L)$ are matrix polynomials in the lag operator L. $\psi(1)$ is the sum of moving average coefficients.

Hasbrouck (1995) notes that the common factor innovation in Equation (10) is the increment, $\psi\varepsilon_t$, with the price change component permanently impounded into the price. He demonstrates that Equation (10) is closely related to Equation (8). 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 $\Omega = FF^T$ to eliminate the contemporaneous relationship, where F is a lower triangular matrix. The information shares are then given as:

$$IS_j = \frac{([\psi F]_j)^2}{\psi \Omega \psi^T}, \quad j = 1, 2, \ldots, n \tag{11}$$

where $[\psi F]_j$ is the j^{th} element of the row of matrix ψF.[20] 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.

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.

3.3.3 Measurement of modified information shares (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

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[20] 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 (11) to calculate the information share.

and contemporaneously correlated.

Lien and Shrestha (2009) propose a modified information shares (MIS) approach that leads to a unique measure of price discovery, as opposed to upper and lower IS bounds.[21] 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 the innovation correlation matrix and Λ as 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 = diag($\sqrt{\Omega_{11}}, \sqrt{\Omega_{22}}, \ldots, \sqrt{\Omega_{nn}}$). Lien and Shrestha (2009) subsequently transform F^* = $[G\Lambda^{-1/2}G^TV^{-1}]^{-1}$ from $\Omega = F^*(F^*)^T$. Under this factor structure, the MIS is given by:

$$IS_j^* = \frac{\psi_j^{*2}}{\psi\Omega\psi^T} \tag{12}$$

where $\psi^* = \psi F^*$. Under this new factor structure, Lien and Shrestha (2009) show that the resultant MIS are independent of ordering, which leads to a measure of price discovery that is order invariant. 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.

3.4 Regression Model

The purpose of this paper is to investigate the change in price discovery of SPDRs. In addition, we also aim to understand the influences of institutional ownership and amount

[21] Prior studies (Fricke & Menkhoff, 2011; Chen & Chung, 2012) examine the price-discovery process using the modified information share approach. They find that results used the modified information share approach are similar with the average results used the information share approach.

of AT and HFT activities on price discovery. Chordia et al. (2011) show the empirical result that several market patterns, including the decline in trade size, the increase in the number of trades, the increased trading in stocks with higher institutional holding, and the heightened sensitivity of turnover to past return, are all consistent with algorithms. Durbin (2010) and Smith (2011) argue that the shrinkage of the average trade size between 2005 and 2009 is consistent with the rapid growth of HFT. Therefore, we examine the change in AT and HFT activities by using the proxy measured as average trade size.

In addition, Chakravarty et al. (2004) argue that price discovery is related to trading volume, spread, and volatility. Boehmer and Kelley (2009) show that price efficiency is directly related to institutional holdings. Following Chakravarty et al. (2004), Ates and Wang (2005), Boehmer and Kelley (2009), and Chen and Chung (2012), this study investigates the change in the price discovery of SPDRs with the following control variables: average trade size, market volatility, institutional ownership, and market liquidity. Thus, the regression model is specified as follows:

$$PD_t = \beta_0 + \beta_1 TrdSize_t + \beta_2 Volatility_t + \beta_3 IO_t + \beta_4 MQI_t + \varepsilon_t \tag{13}$$

where t denotes the date; PD_t denotes the daily share of information for the SPDRs measured by the PT, IS and MIS models for SPDR trades compared with E-mini futures; $TrdSize_t$ is the average size of SPDRs during trading day t; $Volatility_t$ is the realized volatility of the S&P 500 index market in trading day t;[22] IO_t is the institutional ownership of SPDRs in trading day t; and MQI_t is the daily market liquidity for SPDRs during trading day t.

Market quality index (MQI), according to Bollen and Whaley (1998), is defined as

[22] Following Andersen, Bollerslev, Diebold, and Ebens (2001), this study calculates daily realized volatility as follows: (a) the last transaction price at each 5-minute interval is sampled; (b) the price changes of each 5-minute interval is calculated; and (c) the daily realized volatility is the sum of the squared price changes of each day.

the average share depth to the percentage quoted spread:

$$MQI = \frac{(Q_{bid} + Q_{ask})/2}{(P_{ask} - P_{bid})/[(P_{ask} + P_{bid})/2]} \tag{14}$$

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. Furthermore, we argue that *MQI* is more suitable to measure the market impact costs in the SPDR market.

This study adopts the average trade size as a proxy for AT and HFT behavior, and a significantly negative coefficient on the average trade size of SPDRs is expected. Regarding the impact of market volatility on price discovery, Chen and Chung (2012) indicate that a greater share of information will be found in the E-mini futures market in high volatility period. This study argues that the E-mini futures will provide significantly higher contribution to price discovery during high volatility periods because institutional investors or informed traders usually use the derivatives to fulfill the hedge requirement. Therefore, a significantly negative relationship between the information share of SPDRs and market volatility is expected. In addition, informed traders are usually a category of institutional investors. A higher institutional ownership improves the contribution of SPDRs to price discovery, and hence a significantly positive coefficient on the institutional ownership is expected. Finally, according to the transaction cost hypothesis, the reduction in trading costs could enhance the contribution to price discovery. Consequently, a significantly positive coefficient on market liquidity is also expected.

4. Empirical Results

4.1 Summary Statistics in the SPDR Market

Comprehensive details on the number of trades, trade size and transactions by trade size within different trading centers are reported in Table 1. The number of transactions and trading volumes of SPDRs on eleven trading venues are displayed: the AMEX (A, the exchange code in TAQ data), the Boston Stock Exchange (B), the National Stock Exchange (C), the NASD ADF/TRF (D), the International Securities Exchange (I), the Chicago Stock Exchange (M), the NYSE (N), the NYSE-Arca (P), the NASDAQ (T), the Chicago Board of Options Exchange (W), and the Philadelphia Stock Exchange (X).

< Table 1 Inserted about here>

Table 1 shows that over 98% of total transactions and 97% of the total trading volume are concentrated on AMEX, NASD ADF/TRF, NYSE-Arca, and NASDAQ. In particular, most transactions and trading volume are attributable to the NYSE-Arca and NASDAQ. Therefore, the two exchanges are responsible for most of the information on SPDR prices.

Consistent with the 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, we find that the NASDAQ (NYSE-Arca) accounts for 59% (31%) of small trades, 45% (39%) of medium-sized trades and 35% (42%) of block trades. Although the NASDAQ is the most active in terms of small and medium trades, the NYSE-Arca has the relatively active block traders. The examination of price discovery for SPDR trades focuses on a sample of SPDRs traded on the AMEX, NASD ADF/TRF, NYSE-Arca, and NASDAQ.

The inference for the growth of AT and HFT in the SPDR market is also consistent with the findings of prior studies. For example, Hendershott et al. (2011)

show that there is a rapid rise in the growth of algorithmic trading over the 5 years from February 2001 through December 2005.[23] Chordia et al. (2011) recognize that AT is the main determinant of the increases in the share turnover and the number of trades and the reduction in the average trade size observed over the period 1993-2008.[24] Smith (2011) indicates that HFT began to grow rapidly but did not truly take off until 2005 due to the SEC revised Reg NMS with several mandates. Brogaard (2011a) shows that high-frequency traders were involved in 68.49% of all dollar-volume activity in NASDAQ, indicating the prevalence of HFT in the U.S. equity market. Kim and Murphy (2013) examine potential misspecification in four effective spread models for the SPDRs in the period 1997-2009, suggesting that HFT has become increasingly common to split up large orders into many smaller-sized orders and direct them to different trading venues. Accordingly, the phenomenon that the repaid growth of AT and HFT take place in the SPDR market may help explain the empirical results of this study.

<Table 2 inserted about here>

The liquidity analysis of SPDRs using quote data is reported in Table 2. The result shows that the NASDAQ has the highest MQI, indicating that higher liquidity causes a lower market impact cost. This finding is also consistent with the finding of prior studies (Hendershott et al., 2011; Chordia, et al., 2011), in that the increased trading activity has been accompanied by increased market quality in recent years. Accordingly, the study predicts that the NASDAQ will provide the largest

[23] Hendershott et al. (2011) examine the growth of AT and the improvements in liquidity over a 5-year period from 2001 through 2005. They use the rate of electronic message traffic as a proxy for the amount of AT taking place and calculate the number of electronic message per $100 of trading volume as the AT proxy. The two proxies are all raising rapidly over the sample period.

[24] Chordia et al. (2011) indicate that value-weighted average monthly share turnover (on the NYSE) increased from about 5% to about 26% from 1993 to 2008, and the average daily number of transactions increased about ninetyfold during that same period. They conclude that the increased trading activity has been accompanied by increased market quality and recognize that one important technological factor leading to this increase in trading could be the increasing prevalence of AT by hedge funds and other institutions.

contribution to the overall process of price discovery in the S&P 500 ETF market.

5.2 Price Discovery Analyses in the SPDR Markets

This section examines which trading center plays the most important role in the SPDR price-discovery process. Price discovery is modeled in this study using one-second resolution, with lagged terms of up to five minutes, as in Hasbrouck (2003).[25] The trade price is set as the last sale price 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 modified information share measures.

The study examines price discovery of the SPDR market on the six venues (i.e., AMEX, NSX, NASD ADF/TRF, NYSE-Arca, ISE, and NASDAQ). As shown in Table 1, these six venues account for over 99% of all transactions and 98% of the total volume in the sample period. Therefore, the analysis of the price discovery for SPDRs focuses on these venues in the research periods.

<Table 3 inserted about here>

The results of the examination of price discovery in SPDR trades for these venues using the PT, IS and MIS models are reported in Panel A of Table 3, from which we can see that, the NASDAQ accounts for 39.79% of the price discovery in the PT model, 48.22% in the IS model, and 50.33% in the MIS model, contributions that are much higher than those of any of the other venues. This finding shows that the NASDAQ has become the leading exchange in price discovery of the SPDR market. These results are

[25] According to the prior studies (Hasbrouck, 1995, 2003; Kurov & Lasser, 2004; Tse et al., 2006; Chen & Chung, 2012), the price discovery analysis adopts matched time series with one-second intervals between observations. If there is no price reported at a particular second, the previous available price is used. If there are several E-mini trades reported with the same time stamp, only the last trade price is used.

consistent with the study of Chung and Chuwonganant (2012) which finds NASDAQ to offer a faster and higher-success-probability execution than other trading venues, implying that traders are more likely to submit orders to NASDAQ. These results are also consistent with our previous conjecture from the results of Tables 1 and 2, that the NASDAQ provides highest contribution to the overall process of price discovery in the SPDR market owing to the highest market quality index.

This study further examines the price discovery of quoted midpoints on SPDR venues. Table 2 shows that over 97% of NBBO are concentrated on these six venues. The results of the examination of price discovery in SPDR quoted midpoints for these venues are reported in Panel B of Table 3, indicating that the quote prices on the NASDAQ still provide larger contribution than other venues to the overall process of price discovery. Overall, NASDAQ is clearly the dominant contributor to price discovery within the SPDR markets. Egginton et al. (2012) argue the result is the direct outcome of a series of evolution in the consolidation of trading (exchange mergers) adopted by NASDAQ. In addition, Chung and Chuwonganant (2012) show that NASDAQ gained market shares from the NYSE/AMEX and other trading venues after Reg NMS. According to these empirical results, the trade and quote prices on NASDAQ are used to represent SPDR when examining the dynamics of price discovery in the S&P 500 index derivative markets.

5.3 Price Discovery Analyses in the S&P 500 Index Derivatives Markets

The price-discovery results for the S&P 500 index and its derivatives using the PT, IS and MIS models are reported in Table 4. The data, including the E-mini futures prices on the CME, the synthetic spot prices from the index options on the CBOE, the SPDR prices on the NASDAQ, and the synthetic spot prices from the SPDR options on the ISE, are applied to the analyze the S&P 500 index derivatives markets.

<Table 4 inserted about here>

The results of the PT model indicate that SPDR options and SPDRs dominate other markets, with significant contributions to the price-discovery process of 33.01% and 28.65%, respectively. In contrast, the results of the IS and MIS models indicate that the E-mini futures and SPDRs are dominant, contributing approximately 28% and 36% respectively to the price-discovery process. The finding that the SPDRs appear to significant lead the E-mini futures reflects the importance of the SPDRs in the price-discovery process of the S&P 500 index market. This result differs from prior studies (Chu et al, 1999; Hasbrouck, 2003; Tse et al, 2006; Chen & Chung, 2012), which argue the E-mini futures play a dominant role on the price-discovery process, and reemphasizes the significance of the ETF in contributing to price discovery. Furthermore, the finding that the SPDR dominates the price-discovery process in the S&P 500 index market may result from the increase in institutional ownership and the growth of AT and HFT activities. Brogaard (2011b), Hendershott and Riordan (2013) and Brogaard, Hendershott and Riordan (2014) indicate that algorithmic trading and high-frequency trading can improve liquidity and price discovery.[26] Therefore, we conclude that the growth of AT and HFT activities in the SPDR market leads to an increase in its contribution to the price-discovery process.

The empirical results of the IS and MIS models show that the order on the

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[26] Brogaard (2011b) investigates the liquidity and price discovery role of high-frequency traders in U.S. equity markets using data from NASDAQ and BATS exchanges, showing that high-frequency traders are adding to liquidity depth and price discovery. Brogaard, Hendershott, and Riordan (2014) examine a stratified sample of 120 randomly selected stocks listed on NASDAQ and the NYSE, indicating that overall high-frequency trading increase the efficiency of prices by trading in the direction of permanent price changes and in the opposite direction of transitory pricing errors. In addition, Hendershott and Riordan (2013) also show that algorithmic traders contribute more to the efficient price by placing more efficient quotes and they demanding liquidity to move the prices towards the efficient price.

contribution to price discovery is as follows: SPDRs (36%), E-mini index futures (28%), SPDR options (23%), index options (9%) and spot index (4%). Surprisingly t the index options contribute little to price discovery in the S&P 500 index market. There are four possible explanations. First, Stephan and Whaley (1990) show that option price changes do not lead stock price changes, indicating that option market trading is predominantly due to return/risk management motives rather than individuals acting on new information. Second, Fleming et al. (1996) argue that option transaction prices need not adjust until the deviation between the stock and stock option prices is large enough for profitable arbitrage. Moreover, such arbitrage opportunities may never appear, when trading costs are incorporated into the arbitrage trading. Third, Lee and Yi (2001) suggest that the options market is the primary venue for information trading only for small investors, whereas large investors do not necessarily prefer trading in options to trading in stocks when they are informed. Finally, a growing literature shows that S&P 500 index options are mispriced or not efficiently priced relative to a large class of rational option pricing models (Jackwerth, 2000; Ait-Sahalia, Wang & Yared, 2001; Bondarenko, 2003; Constantinides, Jackwerth & Perrakis, 2009). Further, in the study of Constantinides, Jackwerth and Perrakis (2009) argue that there is no evidence to show the options markets becoming more rational over time. In this study, we argue the options prices to contribute little to price discovery due to non-tradable characteristic of the underlying asset.

Table 4 also shows that SPDR options contribute significant information of price discovery in the S&P 500 index market. This finding is consistent with the empirical result provided by Chakravarty et al. (2004), implying that informed investors trade in both spot and options markets and options play an important informational role in the price-discovery process. Since SPDR options contribute significant information of price discovery in the S&P 500 index market, the tradable characteristic in underlying assets may be an important explanation on difference of price discovery between index options and SPDR options.[27] Chakravarty et al. (2004) point out that informed traders usually trade simultaneously in both the underlying security and derivatives markets in order to exercise certain trading strategies. In addition, arbitrageurs can easily replicate arbitrage trading strategies by simultaneously using both the derivatives and the underlying securities. Simultaneous trading in both the underlying security and options markets mitigate the model risk of options pricing models. Accordingly, the transaction costs on the trading strategy exercised SPDRs and SPDR options are less than that between spot index and index options.

We further examine the price discovery in the S&P 500 index derivatives markets by using SPDR quoted prices. The price discovery results for SPDR quoted prices and other index derivatives are reported in Panel B of Table 4. The results indicate that relative to the other derivative markets, the quoted prices of SPDRs in the three models are quite dominant, with significant contributions to the price-discovery process of 49.16% (PT), 57.11% (IS), and 59.33% (MIS) in the sample period. Comparing the results in the SPDR quotes with that in the SPDR trades, SPDR quoted prices play a more important role in the price discovery process.

5.4 Leverage Effect Analysis on the S&P 500 Index Derivatives

Leverage hypothesis argues that informed traders tend to trade in high-leverage markets; therefore, high-leverage securities such as futures and options provide leading information and better price discovery. Prior studies show that the futures markets lead over both the spot and the options markets in the price discovery process.

[27] Stock options used in the study of Chakravarty et al. (2004) also have the tradable characteristic in their underlying assets.

From the viewpoint of the leverage hypothesis, de Jong and Donders (1998) indicate that although both options and futures involve leveraged positions in the underlying asset, this leverage effect is about twice as larger for futures as for (short maturity and at-the-money) call options. The leverage hypothesis still plays an important role, despite that many studies argue that the main determinant factor of the price discovery is the level of transaction costs.[28] In this study, we argue that derivatives usually provide more information in high volatility periods than that in normal volatility periods because informed traders tend to exercise their leading information using the financial instruments with leverage characteristic to satisfy their hedging positions. In this section, the impact of leverage effect on the price-discovery process is investigated with respect to market volatility.

To estimate index derivatives' contribution to the price discovery process in high volatility periods, we classify trading days into different high volatility days according to their daily realized volatility. Following the method provided by Ates and Wang (2005), the procedure we used consists of three steps. First, the daily realized volatility of S&P 500 index market is estimated for each trading day. Second, we estimate empirical distributions of daily realized volatility for the whole sample periods. Third, two different definitions of high volatility days are considered. A trading days during a given sample period is classified as a high volatility day if the daily volatility is greater than the 90th (or 95th) percentile of the empirical distribution of daily realized volatility for the sample period.

<Table 5 inserted about here>

Table 5 presents the analysis of the leverage effect on price discovery based on the comparisons between regular futures, E-mini futures, index options, SPDR options

[28] For example, Chen and Chung (2012) indicate the importance of the leverage hypothesis for the analysis of price discovery in high-volatility period by examining information shares of E-mini futures and SPDRs.

and SPDRs under different definitions of high volatility periods. Comparing the results of Panel A with Panel B and Panel C, the index derivatives with leverage effect provide higher contribution of price discovery in high volatility periods than that of whole periods except for SPDR options using PT model in Panel B. In summary, the results of Table 6 is consistent with the finding of Chen and Chung (2012) showing that the leverage effect in the price discovery analysis is strengthened in high volatility periods. That is, the leverage hypothesis still plays an important role in the determinants of the price-discovery process.

5.5 Regression Analyses in Price Discovery of SPDRs

This study suggests that the contribution made by SPDRs to price discovery is related to its institutional ownership and AT and HFT activities. Table 6 presents change patterns in price discovery and institutional ownership of SPDRs during different sub-sample periods. The sample period is classified as four sub-periods. The result shows that there is a positive relationship between price discovery and institutional ownership. Furthermore, the highest institutional ownership in the sub-period 2 is also accompanied with the highest contribution of SPDRs to price discovery.

<Table 6 inserted about here>

In order to provide support for the argument that the improvement in the contribution of SPDRs to price discovery is caused by changes in institutional ownership and AT and HFT activities, a regression analysis is performed. The results are presented in Table 8.

<Table 7 inserted about here>

The coefficients on the *IO* variable reveal significant explanatory power on the price discovery measures. This result is consistent with Boehmer and Kelley (2009).

Institutional holdings are related to more efficient prices even after considering the role of trading, suggesting that the contribution of SPDRs to price discovery is related to its institutional ownership. Furthermore, this study conjectures that the improvements in the contribution of SPDRs to price discovery are resulted from the institutional investors trading SPDRs by using AT and HFT. The average trade size is used to proxy the measure for amount of AT and HFT activities. The coefficients on the average trade size of SPDRs are found to be negative, indicating that AT and HFT activities enhance price discovery. This result is also consistent with Carrion (2013) and Brogaard, Hendershott, and Riordan (2014) who show that HFT facilitate price efficiency. The coefficients on the MQI variable reveal significantly positive explanatory power on the trade price-discovery measures, implying that the transaction costs hypothesis is helpful to explain the effect of market liquidity on price discovery.

This study further examines the influences of an increase in institutional ownership and the amount of AT and HFT activities on the changes in quote price discovery. The results of Table 8 present that the coefficients on the *IO* variable reveal its significant explanatory power on the quote price-discovery measures except for PT model, suggesting that the quote price-discovery is related to institutional ownership. However, the coefficients on the average trade size of SPDRs are found to be insignificantly negative, hence AT and HFT do not contribute to quoted price discovery. In addition, the coefficients on the MQI variable are significantly positive, implying that the improvements in quote price discovery are also affected by the rise in market liquidity.

6. CONCLUSIONS

The recent trends in trading activity, such as decreased trading costs and increased share turnover, have been proven to significantly affect market efficiency. Following the uptrend in institutional investor trading, this study examines the dynamics of price discovery between the S&P 500 index and its four most active derivative products (i.e., E-mini index futures, index options, ETFs, and ETF options), discuss different hypotheses about price discovery and examine whether the increased institutional holding and the existence of the associated derivatives help promote the completeness and efficiency of the overall market. The empirical results show that the SPDR significantly leads the E-mini futures, reflecting the importance of the SPDR in the price-discovery process in the S&P 500 index market. This result differs from prior studies (Chu et al, 1999; Hasbrouck, 2003; Tse et al, 2006; Chen & Chung, 2012), which argue the E-mini futures play a dominant role on the price-discovery process, and reemphasizes the significance of the ETF in contributing to price discovery. We also show that the improvements in the contribution of SPDRs to price discovery are positively related to its institutional ownership. This result is consistent with the evidence that institutional holdings are related to more efficient prices provided in Boehmer and Kelley (2009). Regarding venues competitions, Tse et al. (2006) and Chen and Chung (2012) show that the ArcaEx ECN dominates all other venues in the price discovery of SPDRs. In contrast, this study shows that the dominant contribution to price discovery within the SPDR markets has transferred to NASDAQ.

In addition, this study examines the influence of the leverage hypothesis in the S&P 500 index market, showing that the index derivatives, i.e., index futures, index options, and ETF options, all provide larger contributions to price discovery in high-volatility periods than in normal-volatility periods, thereby highlighting the importance of the leverage hypothesis for the analysis of price discovery in high-volatility periods.

Finally, upon applying the regression analysis to trade and quote price discovery, this study further finds that the contribution of SPDRs to price discovery is positively related to its institutional ownership and the amount of AT and HFT activities. Overall, the findings of this study are consistent with the viewpoints of Boehmer and Kelly (2009), Chordia et al. (2011), Hendershott and Riordan (2013), and Brogaard, Hendershott, and Riordan (2014). The rapid growth of AT and HFT activities traded by institutional investors under a more complete and perfect market environment helps improve price discovery and enhance price efficiency.

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Table 1 Number of Transactions and Trading Volume for SPDRs in Different Trading Centers

Trading Centers	Total Number of Trades	%	Total Trade Volume (100 shares)	%	Avg. Trade Size (100 shares)	Transactions by Size (shares): Small Size (≤ 1,000)	%	Medium Size (1,001 – 9,999)	%	Large Size (≥ 10,000)	%
A (AMEX)	468,898	1.28	3,960,599	1.54	8.45	403,812	1.21	61,404	2.16	3,682	2.43
B (Boston)	18,580	0.05	48,541	0.02	2.61	18,064	0.05	513	0.02	3	0.00
C (NSX)	255,335	0.70	1,682,369	0.65	6.59	221,737	0.66	32,670	1.15	928	0.61
D (NASD ADF/TRF)	2,605,161	7.14	49,266,927	19.14	18.91	2,263,348	6.76	318,932	11.24	22,881	15.11
I (ISE)	311,162	0.85	1,656,377	0.64	5.32	278,817	0.83	31,968	1.13	377	0.25
M (Chicago)	6,032	0.02	1,842,024	0.72	305.38	4,517	0.01	268	0.01	1,247	0.82
N (NYSE)	95,618	0.26	732,827	0.28	7.66	82,244	0.25	12,597	0.44	777	0.51
P (NYSE-Arca)	11,658,032	31.95	90,117,150	35.00	7.73	10,488,875	31.31	1,105,070	38.95	64,087	42.32
T (NASDAQ)	21,034,293	57.64	106,720,111	41.45	5.07	19,716,619	58.85	1,264,174	44.55	53,500	35.33
W (CBOE)	38,573	0.11	1,284,664	0.50	33.30	24,789	0.07	9,908	0.35	3,876	2.56
X (Philadelphia)	2,089	0.01	136,019	0.05	65.11	2,012	0.01	4	0.00	73	0.05
Overall	36,493,773	100.00	257,447,608	100.00	7.05	33,504,834	100.00	2,837,508	100.00	151,431	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 National Stock Exchange (C), NASD ADF/TRF (D), the International Securities Exchange (I), the Chicago Stock Exchange (M) the NYSE (N), the NYSE-Arca (P), the NASDAQ (T), the Chicago Board Options Exchange (W), and the Philadelphia Stock Exchange (X). This table reports the total number of trades, percentage of transactions, total trade size, percentage of volume, average trade size, and transactions by trade size (small, medium, and large) in different trading centers for SPDRs.

Table 2 Summary Statistics of SPDRs

Trading Centers	National Best Bid and Offer (NBBO) No. of Quotes	%	Average Quoted Depth (x100 shares)	Quoted Spread	Relative Quoted Spread (%)	Market Quality Index (MQI)
A (AMEX)	5,203,998	3.81	111.75	0.0503	0.0341	20.10
B (Boston)	2,729	0.00	13.08	0.4934	0.3307	0.42
C (NSX)	21,657,445	15.87	361.74	0.0216	0.0145	137.71
D (NASD ADF/TRF)	4,391,883	3.22	137.97	0.0697	0.0468	24.10
I (ISE)	20,020,479	14.67	130.73	0.0290	0.0194	52.73
M (Chicago)	48,957	0.04	547.45	0.1480	0.0970	42.77
N (NYSE)	1,586,350	1.16	53.63	0.1087	0.0737	4.72
P (NYSE-Arca)	26,776,546	19.62	453.40	0.0138	0.0093	245.74
T (NASDAQ)	54,929,698	40.25	452.77	0.0130	0.0087	259.66
W (CBOE)	1,735,109	1.27	384.32	0.2130	0.1432	32.97
X (Philadelphia)	117,722	0.09	2.02	0.0406	0.0277	0.38
Overall	136,470,916	100.00	362.19	0.0239	0.0160	184.35

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 market quality index (MQI) is calculated as [QD/2/100] / [PQS×100], where M is the midpoint of the bid and ask prices of the quotes.

Table 3 Price Discovery Analysis in SPDR Markets: AMEX, NSX, NASD ADF/TRF, NYSE-Arca, ISE, and NASDAQ

	AMEX	NSX	NASD ADF/TRF	NYSE -Arca	ISE	NASDAQ
Panel A:SPDR Trade Price						
PT Model	0.0696	0.1501	0.0375	0.2259	0.1190	0.3979
IS Model	0.0217	0.0881	0.0365	0.3092	0.0623	0.4822
MIS Model	0.0214	0.0873	0.0330	0.2936	0.0614	0.5033
Panel B: SPDR Quote Price						
PT Model	0.1032	0.2131	0.0746	0.1595	0.1932	0.2564
IS Model	0.0903	0.2067	0.0923	0.1717	0.1957	0.2433
MIS Model	0.0715	0.2062	0.0907	0.1579	0.2049	0.2688

Note: The results of trade and quote price discovery using the common factor (PT), information share (IS) and modified information share (MIS) models are reported for the AMEX, NSX, NASD ADF/TRF, NYSE-Arca, ISE and NASDAQ. The statistics are based on a VECM of prices for SPDRs estimated as one-second resolution data. The models are estimated for each day during our sample period (from 12 February, 2007 to 31 October, 2007). The daily estimates are calculated from the average of price-discovery measures of all permutations of order of variables in the estimation process. The figures throughout the table are the means of the daily measures of price discovery.

Table 4 Price Discovery Analysis in S&P 500 Index Derivatives Markets

	S&P 500 Index	E-mini Futures	Index Options	SPDRs	SPDR Options
Panel A: SPDR Trade Price					
PT Model	0.1101	0.1475	0.1258	0.3301	0.2865
IS Model	0.0391	0.2840	0.0856	0.3573	0.2340
MIS Model	0.0391	0.2838	0.0838	0.3585	0.2347
Panel B: SPDR Quote Price					
PT Model	0.1037	0.0869	0.1180	0.4916	0.1997
IS Model	0.0389	0.1558	0.0762	0.5711	0.1580
MIS Model	0.0389	0.1377	0.0747	0.5933	0.1555

Note: The results of price discovery using common factor (PT), information share (IS) and modified information share (MIS) models are reported for the S&P 500 spot index, E-mini futures, index options, ETFs and ETF options. The statistics are based on a VECM of prices for these variables estimated as one-second resolution data. The models are estimated for each day during our sample period (from 12 February, 2007 to 31 October, 2007). The daily estimates are calculated from the average of price-discovery measures of all permutations of order of variables in the estimation process. The figures throughout the table are the means of the daily measures of price discovery.

Table 5 Analysis of Leverage Hypothesis Based on a Comparison Between the S&P 500 Index Derivatives and SPDRs under Different High Volatility Periods

	Regular Futures vs. SPDRs	E-mini Futures vs. SPDRs	Index Options vs. SPDRs	SPDR Options vs. SPDRs
Panel A: Whole sample periods (12 February 2007-31 October 2007)				
PT Model	0.1864	0.3179	0.2276	0.4369
IS Model	0.0729	0.4420	0.1562	0.3593
MIS Model	0.0728	0.4406	0.1539	0.3560
Panel B: The 90th quantile of daily volatility distribution for whole sample periods (σ > 19.28%)				
PT Model	0.2482	0.4476	0.2725	0.4218
IS Model	0.1445	0.5288	0.1849	0.3726
MIS Model	0.1444	0.5272	0.1822	0.3640
Panel C: The 95th quantile of daily volatility distribution for whole sample periods (σ > 24.39%)				
PT Model	0.3392	0.5430	0.3239	0.5305
IS Model	0.2463	0.6314	0.2774	0.4828
MIS Model	0.2463	0.6330	0.2761	0.4748

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 derivatives with leverage effect (i.e., regular and E-mini futures, index options and SPDR options) respective compared with SPDRs under different volatility periods. The daily realized volatility of S&P 500 index market is estimated for each trading day. Trading days during a given sample period are classified into different high volatility days if their daily volatility is greater than the 90th and 95th percentile of the empirical distribution of daily realized volatility for a given sample period. The statistics are based on a vector error correction model of prices for S&P 500 index and derivatives estimated as one-second resolution data. The models are estimated for each day during our sample period (from 12 February, 2007 to 31 October, 2007). The daily estimates are calculated from the average of price-discovery measures of all permutations of order of variables in the estimation process. The figures throughout the table are the means of the daily estimates.

Table 6 Price Discovery Analysis and Institutional Ownership of SPDRs

Report Date	Institutional Ownership	SPDR Trade Prices vs. E-mini Futures			SPDR Quote Prices vs. E-mini Futures		
		PT Model	IS Model	MIS Model	PT Model	IS Model	MIS Model
(1) March 31, 2007	58.87%	0.6423	0.4956	0.4962	0.8430	0.7360	0.7476
(2) June 30, 2007	76.08%	0.7500	0.6312	0.6339	0.8738	0.8159	0.8312
(3) September 30, 2007	66.75%	0.6395	0.5255	0.5262	0.8458	0.7960	0.8376
(4) December 31, 2007	70.15%	0.6741	0.5411	0.5421	0.8573	0.7910	0.8213

Note: This table shows the institutional ownership of SPDRs under different report dates. The results of trade and quote price discovery using the common factor (PT), information share (IS) and modified information share (MIS) models are reported for SPDR trades and compared with E-mini futures prices under different sub-periods. The sample period for price discovery analysis is classified as follows: (1) 12 February 2007-31 March 2007; (2) 1 April 2007-30 June 2007; (3) 1 July 2007-30 September 2007; and (4) 1 October 2007-31 October 2007. The statistics are based on a vector error correction model of prices for SPDRs and E-mini futures estimated as one-second resolution data. The models are estimated for each day during different sub-periods. The daily estimates are calculated from the average of price-discovery measures of all permutations of order of variables in the estimation process. The figures throughout the table are the means of the daily estimates.

Table 7 Regression Analyses of Trade and Quote Price Discovery for SPDRs

	SPDR Trades vs. E-mini Futures			SPDR Quotes vs. E-mini Futures		
	PT Model	IS Model	MIS Model	PT Model	IS Model	MIS Model
TrdSise	-0.0431** (-2.3743)	-0.0407* (-1.9063)	-0.0405* (-1.8432)	-0.0146 (-1.5660)	-0.0164 (-1.2541)	-0.0199 (-1.4271)
Volatility	-0.2509 (-0.6192)	0.1620 (0.3458)	0.1568 (0.3155)	-0.2092 (-0.6851)	0.4397 (1.1390)	0.7288 (1.6482)
IO	0.5123* (1.7690)	0.9160** (2.4818)	0.9373** (2.4803)	0.2404 (1.2348)	0.7799*** (2.6693)	0.8417*** (2.7680)
MQI	0.7298*** (3.9800)	0.9482*** (3.8353)	0.9606*** (3.7514)	0.2638* (1.9687)	0.5388*** (3.0003)	0.5247*** (2.6490)
Constant	0.5116** (2.0536)	0.0018 (0.0054)	-0.0151 (-0.0447)	0.7647*** (4.7764)	0.2116 (0.8950)	0.1896 (0.7617)
Adj. R^2	0.1874	0.1257	0.1197	0.0853	0.0511	0.0520

Note: The changes in the contribution of SPDRs to price discovery are tested based on the following regression model (Equation 13):

$$PD_t = \beta_0 + \beta_1 TrdSize_t + \beta_2 Volatility_t + \beta_3 IO_t + \beta_4 MQI_t + \varepsilon_t \quad (13)$$

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 and quotes compared with E-mini futures prices; $TrdSize_t$ is the average trade size of SPDRs during trading day t; $Volatility_t$ is the realized volatility of the S&P 500 index market; and IO_t is the institutional ownership of SPDRs using the average ratio on report date before and after trading day t; MQI_t is the SPDR market quality index during trading day t. The total number of observations is 181 trading days. 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.

Table A1 Estimated Costs of Trading E-mini S&P 500 Index Futures versus SPDRs

	E-minis	**SPDRs**
Commission	0.8	2.8
1-Way Market Impact/Transaction Cost	6.0	6.0
Total Entry Cost	**6.8**	**8.8**
ETF Management Fee	—	10.0
Futures Roll Costs	2.5	—
Additional Commission from Roll	5.0	—
Total Holding Cost	**7.5**	**10.0**
Commission	0.8	2.8
1-Way Market Impact/Transaction Cost	6.0	6.0
Total Exit Cost	**6.8**	**8.8**
Total Cost for 1 Year	**21.1**	**27.5**

Note: Goldman Sachs tallied up the costs associated with E-mini futures and SPDRs, concluding that the cost of holding a $100 million position for one year in E-mini S&P 500 index futures totaled 21.1 basis points annually versus 27.5 basis points for SPDRs. Data source is obtained from the research report "Goldman Sachs Global Derivatives and Trading Research (July 26, 2004)".