Funding Liquidity and Market Quality: Evidence from the S&P 500 ETF and Index Futures

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ABSTRACT

This paper aims to analyze the market quality in the period of credit crunch in 2007 by examining the impact of funding liquidity on market liquidity and price discovery of S&P 500 ETF (SPDRs) and index futures (E-minis). Empirical results reveal that funding illiquidity affects market liquidity and there is a significant effect of liquidity spillover between SPDRs and E-minis during the subprime crisis period. Specially, the impact of funding illiquidity on market liquidity is offset by spillover effects between the two markets in the period of credit crunch. In addition, SPDRs appear to significantly lead the E-mini futures in the price-discovery process, reflecting the importance of the SPDR in the price-discovery process in the S&P 500 index market. E-minis with leverage characteristic still play an important role in the price-discovery process during the high volatility period. Considering the effects of other market factors on price discovery, the regression results suggest that changes in contribution of SPDRs and E-minis to price discovery are mixed because of the liquidity spillover effects. The empirical result is helpful to understand the impacts of funding liquidity on market liquidity and price discovery of SPDRs and E-minis.

Keywords: Funding liquidity, Market quality, ETF, Index futures, Price discovery, Market liquidity, Spillovers

JEL Classification: G13, G20, C32

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1. INTRODUCTION

The fact of portfolio insurers continuing to short index futures and most other investors liquidating their positions on October 20, 1987 is because of uncertainty concerns (Gammill & Marsh, 1988). During the financial crisis, particularly at the times of specific bankrupt event, the liquidating and hedging needs of short positions emerged due to the reason of the concerns about the unscheduled trading halts and the uncertainty about the clearinghouse integrity. Their short strategies of reducing equity exposures are well recognized by market professionals, further deteriorating the market fluctuation. The amplification of volatility therefore causes incomplete protection for considerable needs of insurance and liquidating spiral.

Stressed markets produce a greater number of cash/futures arbitrage opportunities than do non-stressed markets (Cheng & White, 2003). Margin requirements increased in illiquidity when margin-setting financiers are unsure whether price changes are due to fundamental news or to liquidity shocks (Brunnermeier, 2009). Grossman and Miller (1988) argue that both spot and futures stock markets were highly illiquid on October 19, 1987, the day of the crash. Such uncertainty happens particularly when a liquidating pressure leads to price volatility, which raises the financier's expectation about future volatility, and this leads to increased margins. Furthermore, the "Flash Crash" of May 6, 2010 represents one of the most dramatic events in the history of the financial markets.[1] The report from the Commodities Future Trading Commission (CFTC) and the Securities and Exchange Commission (SEC) identifies one source of the flash crash as those index arbitrageurs who opportunistically buy E-minis and simultaneously sell products like SPDRs or individual equities in the S&P 500, which transferred the selling

[1] In the late afternoon of May 6, major U.S. equity market indexes began to decline sharply. In the course of about 30 minutes, stock indices, index futures, index options and ETFs experienced a sudden price drop of more than 5%, followed by a repaid rebound.

pressure in the futures market to the equities markets.

This study analyzes the change of market quality in the period of credit crunch during 2007 by examining the impact of funding illiquidity on market liquidity and price discovery of the S&P 500 ETF (SPDRs) and E-mini index futures (E-minis). The interaction between funding liquidity and market liquidity has been analyzed in numerous studies (Brunnermeier & Pedersen, 2009; Chiu, Chung, Ho, & Wang, 2012); however, to date there is no study within the literature considering the impact of funding liquidity on price discovery and the influence of spillover effects on market liquidity. To fill the gap, we set out in this study to examine the impact of funding illiquidity on changes of market quality in the SPDR and E-mini index futures markets by discussing the liquidity linkage and illiquidity spillover between the two markets.

The issue of liquidity co-movement has received much attention and discussion by developing theoretical models (Brunnermeier & Pedersen, 2009; Cespa & Foucault, 2014; Goldstein, Li, & Yang, 2014). Brunnermeier and Pedersen (2009) provide a model that links an asset's market liquidity and traders' funding liquidity, showing that margins are destabilizing and market liquidity and funding liquidity are mutually reinforcing, and leading to liquidity spirals. Cespa and Foucault (2014) show how liquidity spillovers arise in a two asset framework when dealers specialized in different assets learn from others' prices, exploring that there is a self-reinforcing, positive relationship between illiquidity of the two assets. Furthermore, Goldstein, Li, and Yang (2014) use a setting similar to Cespa and Foucault (2014) to analyze a model in which traders have different trading opportunities and learn information from prices, showing that the diversity of trading motives (speculation or hedging) may reduce the informativeness of the price and increase the cost of capital.

In addition to the theoretical studies previously mentioned, empirical studies reveal that market declines cause asset illiquidity and binding capital constraints lead to sudden liquidity dry-ups. Hameed, Kang, and Viswanathan (2010) find that negative market returns decrease stock liquidity, especially during times of tightness in the funding market. Chiu, Chung, Ho, and Wang (2012) show that a higher degree of funding illiquidity leads to a decline in market liquidity in the ETF market, especially for the financial ETFs than the index ETFs.

Although the relationship between funding liquidity and market liquidity has been analyzed in these previous studies, they also remain some suggestions for future research. First, Hameed, Kang, and Viswanathan (2010) suggest that future research would be to investigate the effect of funding constraints using high frequency data because their evidence is indirect. Second, Cespa and Foucault (2014) provide a suggestion for future research on the strength and influence of liquidity spillovers across asset classes. Third, Goldstein, Li, and Yang (2014) provide an example by using the index futures markets, indicating that individual traders are more likely to concentrate on trading of the stock index, while hedge funds are more likely to engage in index arbitrage by trading in both the equity and index futures markets. Integrating these research suggestions, this study analyzes the impact of funding illiquidity on changes of market quality in the SPDR and E-mini index futures markets.

Consistent with Brunnermeier and Pedersen (2009) and Chiu, Chung, Ho and Wang (2012), we show that funding liquidity significantly affects market liquidity of SPDRs and E-minis. This study also presents that there is a significant liquidity spillover between SPDRs and E-minis in the period of credit crunch. Although Prior studies argue that the E-mini index futures dominate the price-discovery process (Chu, Hsieh & Tse, 1999; Hasbrouck, 2003; Tse, Bandyopadhyay & Shen, 2006;

Chen & Chung, 2012), the empirical results reveal that SPDRs dominate the price-discovery process in the S&P 500 index markets during the sample period. We also show that E-minis with leverage characteristic still play an important role in the price-discovery process during the high volatility period. This result strengthens the importance of the leverage hypothesis on the price-discovery analysis. In addition, we find the influence of funding illiquidity on the contribution of E-mini index futures to price discovery is higher that of SPDRs. However, considering the aggregate effects of other market factors (i.e., market volatility, trading frequency, and market liquidity) on the contribution to price discovery, we suggest that E-mini index futures have more contributions to price discovery in the period of credit crunch than that in the normal period. Based upon these results, we show the important influence of funding liquidity on market liquidity and price discovery for SPDRs and E-minis.

The remainder of this paper is organized as follows. A review of the related literature is presented in the next section, followed by a discussion of the data and research methodology adopted for our study. The penultimate section presents the empirical results of our research, with the final section offers conclusions drawn from this study.

2. LITERATURE REVIEW

The mispricing is found with the evidence in the index futures daily data (Mackinlay & Ramaswamy, 1988; Yadav & Pope, 1990). However, after considering transaction costs with intraday data, Ho, Fang and Woo (1992) find that the arbitrage opportunities are weak, and the mispricing is quickly corrected.

Irrational psychological behavior may cause investors to overreact or underreact to information, leading to a continuous mispricing. This may result in a short term liquidity problem, as the human psyche tends to prefer the status quo under uncertainty. Informed traders trying to lock in arbitrage profits may face resistance from liquidity providers who, according to Easley and O'Hara (1992), are less informed. Therefore, when the market is under pressure, reaching a market consensus for security prices would be much slower compared with that of a normal market, leading to a longer time between trades and greater mispricing for index futures transactions.

Finance scholars have long recognized that deviations from no-arbitrage relations are related to the frictions associated with transacting, in particular to liquidity indicators such as the bid–ask spread. Thus, financial market liquidity may play a key role in moving prices to an appropriate level, where the futures-cash basis is zero (Roll, Schwartz & Subrahmanyam, 2007). They also suggest that during financial crises, market conditions can be severe and liquidity can decline or even disappear.

There will likely be increases in illiquidity and profitable arbitrage opportunities in stressed and down markets (Cheng & White, 2003), and it is more difficult to react quickly. In stressed and down markets, liquidity suppliers are less likely to take the opposite side of an arbitrage strategy against the informed (institutional) traders, perhaps due to confusion as to what is happening in the marketplace. This, in turn, leads to higher arbitrage profits, as mispricing tend to persists under stressful conditions. Although pricing inefficiencies increase under stressful conditions and are persistent, it is unclear that whether such inefficiency during the 2007-2008 financial crisis can be attributed to the credit default in the money markets.

However, the funding of traders affects and is affected by market liquidity in a profound way. Based on the links between finding and market liquidity, Brunnermeier and Pedersen (2009) develop a model to explain that market liquidity (i) can suddenly dry up, (ii) has commonality across securities, (iii) is related to volatility, (iv) is subject to "flight to quality", and (v) co-moves with the market. Their analysis implies that central banks can help mitigate market liquidity problems by controlling funding liquidity.

In addition, Hameed, Kang and Viswanathan (2010) investigate the impact of market declines on various dimensions of liquidity, including: (i) time-series as well as cross-sectional variation in liquidity; (ii) commonality in liquidity; and (iii) cost of liquidity provision. Consistent with the result of previous theoretical model, their results suggest that market liquidity drops after large negative market returns because aggregate collateral of financial intermediaries falls and many asset holders are forced to liquidity, making it difficult to provide liquidity precisely when the market needs it.

The liquidity in the stock market affects and is affected by pricing efficiency of index futures. Many studies had argued that the stock returns are cross-sectionally related to liquidity (Jacoby, Fowler & Gottesman, 2000; Amihud, 2002; Pastor & Stambaugh, 2003). Therefore, the stock returns affected by liquidity would further influence the cash-futures arbitrage opportunities. For example, order imbalances resulting from arbitrage trades may have a persistent impact on stock market liquidity (Chordia, Roll, & Subrahmanyam, 2002). In addition, less profitable cash/futures arbitrage is consistent with higher liquidity, and that, during periods of liquidity shocks caused by market stresses, a slowing in the price discovery will lead to slower mean reversion in the arbitrage basis (Kumar & Seppi, 1994).

The pricing inefficiency is positively related to the volatility. Cheng and White (2003) indicate that the volatility and investors' sentiment are high under the stressful market, further affecting the pricing efficiency. Koutmos (1999) find that bad news (measured by negative returns) is incorporated faster into current prices than good news (measured by positive returns). Such a phenomenon of faster adjustment of prices to negative returns leads us to hypothesize that arbitrage profits may be higher under a down market. Therefore, this study suggests that a market under stressed (as proxied by higher volatility and greater price changes) may demonstrate a lower pricing efficiency and a more persistent arbitrage profit than a normal market.

Unlike commercial banks Bear did not have access to the Federal Reserve discount window and was solely dependent upon the market for its liquidity and funding. During the market disruptions of 2007, broker-dealers' financing and liquidity arrangements attracted an increasing level of attention from analysts. The credit ratings agencies note these recent market pressures that the major U.S. broker-dealers have been liquidity-challenged in third-quarter 2007, when disruptions in the U.S. subprime space and the spillover into other markets contributed to a general and widespread market correction.

3. DATA AND RESEARCH METHODOLOGY

3.1 Data Description

The ETF used as index proxy is the S&P 500 Depositary Receipts (SPDRs). The prices of SPDRs are 1/10th of the S&P 500 index level. The data on ETFs, which include the tick-by-tick trade prices, trading volume, quote prices, and quote sizes 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 sample covers the period from 12 February 2007 to 31 December 2007, a period which spans about six months ("First Period") prior to, and about five months ("Second Period") after, the start of the credit crunch as 9

August 2007.

A comprehensive introduction to the market structures of index futures and ETFs has already been provided in many prior studies.[2] Briefly, S&P 500 index regular futures are traded on the open outcry floor of the Chicago Mercantile Exchange (CME) while 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 a day. As such, E-mini futures are designed for individual or small investors. Chu et al. (1999), Hasbrouck (2003), and Tse et al. (2006) demonstrate that E-mini index futures appear to play an important role in the price discovery process for the S&P 500 index. Furthermore, Kurov and Lasser (2004) show that E-mini trades initiated by exchange locals are more information than those initiated by off-exchange traders and provide evidence explaining the result of price leadership of the E-mini futures contracts reported by Hasbrouck (2003).

The E-mini version of S&P 500 futures is taken as the index futures. Hasbrouck (2003) and Kurov and Lasser, (2004) find the evidence that the small-denomination futures contracts (E-minis) have higher price discovery capability than floor-traded index futures contracts. The respective contract size of S&P 500 E-mini futures is $50 multiplied by the S&P 500 index level. The data on E-mini futures, which

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

include trade prices and number of trades, are obtained from the intraday database of Tick Data Inc.[3]

ETFs are listed on the AMEX; however, trading in ETFs takes place in multiple venues. On 31 July 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.[4] 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 (Boehmer & Boehmer (2003); Tes & Erenburg (2003)).

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. 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.[5] Chen and Chung (2012) also show that ArcaEx ECN denominates price

[3] The quote data for index futures are unavailable, as is the case in most futures studies.

[4] An 'unlisted trading privilege' (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.

[5] The Pacific Exchange created a coalition with the ArcaEx ECN in 2003 to provide the exchange with the ability to electronically trade listed securities; therefore, prior studies adopt the Pacific Exchange data for the ArcaEx ECN.

discovery of SPDR market after the introduction of SPDR options in 2005.

In March 2006, the NYSE Group merged with ArcaEx to create NYSE-Arca. Although Arca is fully electronic, it is similar to the NYSE in that it allows lead market makers akin to the NYSE specialists to provide liquidity and trading efficiency. Arca also allows buyers and sellers to view a company's open limit order book, displaying orders simultaneously to both buyer and seller, which is something the NYSE's OpenBook does as well.[6]

NASDAQ is an electronic market venue traditionally operated by the National Association of Securities Dealers (NASD).[7] NASDAQ began competing with the ECNs through its SuperMontage electronic trading program developed over the objections of competitors. In September 2004, NASDAQ deepens their liquidity pool by acquiring the Brut ECN. In April 2005, they took the acquisition of the industry's biggest ECN, INET (Instinet-Island/INET) after the NYSE announced its merger with ArcaEx ECN. On August 1, 2006, NASDAQ became operational as a national securities exchange separate from the NASD. On February 12, 2007, they became operational as an exchange in other exchange listed securities as well.[8]

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

6 Euronext merged with the NYSE on April 4, 2007 to form NYSE Euronext and the first global stock exchange. On October 1, 2008, the NYSE completed acquisition of the AMEX.

7 The detail introduction of the NASDAQ is also discussed by Battalio, Egginton, Van Ness, and Van Ness (2011) and Vuorenmaa and Innovations (2012).

8 On November 7, 2007, NASDAQ purchased Philadelphia Stock Exchange for $652 million and the acquisition got finalized in July 24, 2008. On October 2, 2007, NASDAQ agreed to acquire the Boston Stock Exchange for $61 million.

3.2 Measurement of Funding Liquidity

Following the study of Chiu, Chung, Ho and Wang (2012), we use Libor, which is modeled as the spread between the three-month US inter-bank LIBOR rate and the overnight index swap, to measure the capital constraints of the financial intermediaries. In addition, asset-backed commercial papers (ABCP) and Repo in the collateral markets are used to capture hedge funds and the capital constraints of market makers. ABCP is measured as the spread between three-month ABCP rates and the overnight index swap, and Repo is calculated as the mortgage repossession rate minus the government repossession rate.

<Figure 1 Inserted about here>

Figure 1 illustrates the patterns of the daily Libor, ABCP and Repo from 12 February 2007 to 31 December 2007 and reveals that these funding liquidity variables are change in co-movement. Figure 1 also shows a rise pattern in these funding liquidity variables starting on August 2007 and presents that there would have been a strong likelihood of them suffering from funding problems from August 2007 onwards. Accordingly, the Zivot and Andrews (1992) test was used, which tests the null of a unit root against the alternative of a deterministic trend with a structural break, which is estimated endogenously. The Zivot and Andrew (1992) unit root test incorporates an adjustment for the structural break. The results of the Zivot and Andrews (1992) tests show that finding liquidity measures, including ABCP, Libor, and Repo, are all stationary series under considering the a structural break date on August 9, 2007.

3.3 Measurement of Market Liquidity

There are three well-established liquidity benchmarks in the literature. The benchmark is spread (*SP*), calculated this measure as follows:

$$SP = \left(P_{ask} - P_{bid}\right)/P_{mid} \tag{1}$$

where P_{ask}, P_{bid}, and P_{mid} are the ask price, bid price, and midpoint of these two prices, respectively. Since there is no direct bid-ask spreads quote data available for our data from Tick Data database, we computed bid-ask spreads by implementing the methodology suggested in Wang et al. (1994). The estimator, which is also used by the Commodity Futures Trading Commission (CFTC), is calculated as the average absolute price change in the opposite direction.

According to the methodology proposed by Wang et al (1994), the realized bid-ask spreads are estimated as follows: (i) create an empirical joint price distribution of ΔP_t and ΔP_{t-1} during a daily interval; (ii) discard the subset of price changes which exhibit price continuity (i.e., positive change followed by positive change); (iii) take absolute values of price changes that are price reversals, and (iv) compute the mean of absolute values obtained in step (iii). Finally, we can estimate the average bid-ask spread every day during our research period. Consistent with the spread of SPDRs, we divide the average bid-ask spread of E-minis by trade price.

<Figure 2 Inserted about here>

Figure 2 presents the change patterns in market liquidity of SPDRs and E-minis. The figure clearly shows that there is a significant comovement in market liquidity of SPDRs and E-minis.

3.4 Measurement of Price Discovery

As noted by O'Hara (2003), two of the most important functions of financial markets are price discovery and liquidity. Within the prior literature on common factor models, two popular approaches have emerged in the investigation of the mechanics of price discovery. The first is the 'permanent-transitory' (PT) model discussed by Gonzalo and Granger (1995) and the second is the 'information shares' (IS) model developed by Hasbrouck (1995).

Although both the PT and IS models use the VECM as their basis, different definitions of price discovery are adopted in each model. These two models have since attracted considerable attention within the literature, with the relationships and differences between the two models having been discussed at length.[9] 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 of the innovations to the common factor. These two models are directly related and provide similar results if the residuals are uncorrelated between markets; however, they typically provide diverse results in those cases where there is substantive correlation. Numerous studies since then have adopted the two models as the means of examining the contribution of price discovery from closely-related markets.[10] The analysis is based on the information share approach that requires the estimation of the vector error correction model (VECM).

According to Engle and Granger (1987), the representation of vector error correction model (VECM) can be shown as follows:

$$\Delta Y_t = \mu + \Pi Y_{t-1} + \sum_{i=1}^{k} A_i \Delta Y_{t-i} + \varepsilon_t \tag{4}$$

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 are $n \times n$ 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,[11] α is an

[9] See for example, an overview of price-discovery issues are provided by Baillie et al. (2002), de Jong (2002), Lehmann (2002), Harris et al. (2002a), Harris et al. (2002b), and Hasbrouck (2002).

[10] Examples include: Booth et al. (1999), Chu et al. (1999), Hasbrouck (2003), and So and Tse (2004).

[11] About the definition of z_t, this study follows the Hasbrouck (1995; 2003). If there are n securities,

$n \times (n-1)$ matrix of adjustment coefficients, and ε_t is an $n \times 1$ vector of price innovations. The coefficients α of the error correction term measure the price reaction to the deviation from the long-term equilibrium relationship.

3.4.1 Permanent-Temporary (PT) Measure

Gonzalo and Granger (1995) are concerned with the error correction process. This process involves only permanent (as opposed to transitory) shocks that result in a disequilibrium. This 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 each market's contribution to the common factor, where the contribution is defined to be a function of the markets' error correction coefficients.

Stock and Watson (1988) shows that the price vector can be decomposed into a permanent and a transitory component. As demonstrated by Stock and Watson (1988), the common trend of the price series is as follows:

$$Y_t = f_t + G_t \tag{5}$$

where f_t is the common factor and G_t is the transitory component which 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 $f_t = \Gamma' Y_t = \left(\alpha'_\perp \beta_\perp\right)^{-1} \alpha'_\perp Y_t$; 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). This study follow the approach suggested by Gonzalo and Ng (2001) to estimate $\alpha_\perp$ and $\beta_\perp$.

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there are n-1 linearly independent differences, and z_t can be defined as follows:

$$z_t = \left[(Y_{1t} - Y_{2t}) \quad (Y_{1t} - Y_{3t}) \quad \cdots \quad (Y_{1t} - Y_{nt})\right]'$$

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

3.4.2 Information Share (IS) Measure

Hasbrouck (1995) defines price discovery in terms of the variance of the innovations to the common factor. The IS model measures each market's relative contribution to this variance. This contribution is dubbed the market's information share. The process of price discovery is analyzed by using the Hasbrouck (1995) model, which calculates "information shares" as relative contributions of the variance of a security in the variance of 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 and components incorporating effects of market frictions.

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

$$\Delta Y_t = \psi(L)\varepsilon_t, \tag{6}$$

as well as its integrated form:

$$Y_t = Y_0 + \psi(1)\sum_{i=1}^{t}\varepsilon_i + \psi^*(L)\varepsilon_t, \tag{7}$$

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 of

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 (4) is the increment, $\psi\varepsilon_t$, with the price change component being permanently impounded into the price. Hasbrouck 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 $Var(\psi\varepsilon_t)$ which is 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 given as:

$$IS_j = \frac{\left([\psi F]_j\right)^2}{\psi\Omega\psi'}, \quad j = 1, 2, \ldots, n \tag{8}$$

where $[\psi F]_j$ is the j^{th} element of the row of matrix ψF.[12] A market's contribution to price discovery is measured as the market's relative contribution to the variance of the innovation in the common trend. Baillie et al. (2002) show an easier method of calculating information shares directly from the VECM results without obtaining the VMA representation. The calculation of information share is based on VECM method.[13]

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

[12] It should be further noted that Baillie et al. (2002) presented evidence of an important relationship existing 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 (4) to calculate the information share.

[13] See for example, Hasbrouck (2003) and Tse et al. (2006).

(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.

3.4.3 Modified Information Share (MIS) Measure

The results of information shares typically depend on the ordering of 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, and this discrepancy may be large if the series' innovations are highly and contemporaneously correlated. Lien and Shrestha (2009) proposed modified information share (MIS) that leads to a unique measure of price discovery instead of the upper and lower IS bounds. According to the MIS model, the use of the factorization matrix that is based on the correlation matrix is suggested. Lien and Shrestha (2009) define that Φ represent the innovation correlation matrix and Λ represent the diagonal matrix with 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; i.e., V = diag($\sqrt{\Omega_{11}}$, …, $\sqrt{\Omega_{nn}}$). Then, they transform $F^* = \left[G\Lambda^{-1/2}G'V^{-1}\right]^{-1}$ from $\Omega = F^*\left(F^*\right)'$. Under this factor structure, the MIS is given by

$$IS_j^* = \frac{\psi_j^{*2}}{\psi\Omega\psi'} \tag{9}$$

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

3.6 Regression Analysis in Market Liquidity

The purpose of this paper is to investigate the impacts of funding liquidity on market quality of SPDRs and S&P 500 index futures. We examine the influence of funding liquidity on market liquidity of SPDRs and S&P 500 index futures. This study follows prior studies (Bollen & Whaley, 1998; Hameed, Kang, & Viswanathan, 2010; Chordia et al., 2011; Hendershott et al., 2011) to design the regression model by adopting number of trades, market volatility, market return and funding liquidity, all of which are employed as control variables. In order to examine the argument of Cespa and Foucault (2014), we consider the impact of the SPDR's liquidity on the E-mini's liquidity. This study examines the change in the market liquidity of S&P 500 index futures using a regression model as defined in the following equation:

$$FSP_t = \beta_0 + \beta_1 \log(FNT_t) + \beta_2 FSig_t + \beta_3 FRet_t + \beta_4 SSP_t + \beta_5 FundLiq_t + \varepsilon_t \quad (10)$$

where t denotes the daily time interval; FSP_t refers to the daily market liquidity for S&P 500 index futures measured by the spread during trading day t; FNT_t is the number of trades for S&P 500 index futures during trading day t; $FSig_t$ is the Parkinson (1980) extreme value estimator which proxies for the volatility of S&P 500 index futures in trading day t; $FRet_t$ is the return in S&P 500 index futures during trading day t; SSP_t refers to the daily market liquidity for SPDRs measured by the spread during trading day t; and $FundLiq_t$ is the funding liquidity measure, including Libor, ABCP and Repo, in trading day t.

In addition, we also design a regression model to examine the change in the market liquidity of SPDRs using quoted spread (*SSP*) as defined in the following equation:

$$SSP_t = \beta_0 + \beta_1 \log(SNT_t) + \beta_2 SSig_t + \beta_3 SRet_t + \beta_4 FSP_t + \beta_5 FundLiq_t + \varepsilon_t \quad (11)$$

where t denotes the daily time interval; SNT_t is the number of trades for SPDRs during trading day t; $SSig_t$ is the Parkinson (1980) extreme value estimator which proxies for the volatility of SPDRs in trading day t; and $SRet_t$ is the return in SPDRs during trading day t.

To consider the endogeneity of the spreads between SPDRs and E-minis in the liquidity regression models, the models are estimated using the generalized method of moment (GMM) approach, which uses the lagged spread and lagged volatility as the instrumental variables for the spread. This study uses the number of trades as a proxy for market activities, and a negative coefficient on the number of trades is expected. In addition, greater volatility will lead to a greater likelihood of an adverse price move, resulting in a poor liquidity. A negative coefficient on the return variable is expected if negative market return is harmful to market liquidity (Hameed et al. 2010). If market liquidity deteriorates as a result of funding illiquidity, then this indicates an increase in market impact costs. Therefore, a positive coefficient on funding liquidity is also expected.

3.7 Regression Analysis in Price Discovery

The purpose of this paper is to investigate the impacts of funding liquidity on market quality of SPDRs and S&P 500 index futures. Thus, we follow the prior studies (Chakravarty et al., 2004; Ates & Wang, 2005; Chen & Chung, 2012) to control for other factors, by examining the change in market liquidity and price discovery of SPDRs and S&P 500 index futures.

In order to examine the arguments that the change in contribution of SPDRs and S&P 500 index futures to price discovery is associated with the factor, this study designs a regression model to adopt similar control variables which include the number of trades and market volatility. Chakravarty et al. (2004) argue that price discovery is related to number of trades, spread, return, volatility and funding liquidity. We examine the change in the level of price discovery after the date of August 10, 2007 by using a regression model, as defined in the following equation:

$$\log\left(\frac{PD}{1-PD}\right)_t = \beta_0 + \beta_1 \log\left(\frac{SVol}{FVol}\right)_t + \beta_2 \log\left(\frac{SNT}{FNT}\right)_t + \beta_3 \log\left(\frac{SSP}{FSP}\right)_t + \beta_4 Sigma_t + \beta_5 FundLiq_t + \varepsilon_t \quad (12)$$

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 compared with E-mini futures; $SVol_t$ ($FVol_t$) is the trade volume for SPDRs (E-minis) during trading day t; SNT_t (FNT_t) is the number of trades for SPDRs (E-minis) during trading day t; SSP_t (FSP_t) refers to the daily market liquidity for SPDRs (E-minis) measured by the spread during trading day t; $Sigma_t$ is the Parkinson (1980) extreme value estimator which proxies for the volatility of the S&P 500 index market on trading day t; and $FundLiq_t$ is the funding liquidity measure, including Libor, ABCP and Repo, in trading day t.

According to the transaction cost hypothesis, the reduction in trading costs enhances the contribution to price discovery. Consequently, a significantly positive coefficient on market liquidity is also 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 be 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 negative relationship between the information share of SPDRs and market volatility is expected. Informed traders are usually institutional investors. Finally, if market liquidity deteriorates as a result of funding illiquidity, then this indicates an increase in market impact costs. Therefore, a negative coefficient on funding liquidity is also expected.

4. EMPIRICAL RESULTS

4.1 Summary Statistics in the SPDR and E-mini Futures Markets

Comprehensive details on the number of trades, trade size and transactions by trade size within different trading centers in the SPDR market are reported in Table 1. This table depicts the number of transactions and trading volumes of SPDRs on eleven trading venues including: 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 all transactions and 97% of the total trading volume are concentrated on AMEX, NASD ADF/TRF, NYSE-Arca, and NASDAQ in the first and second periods, respectively. In particular, most of all transactions and trading volume are attributable to the NYSE-Arca and NASDAQ. Clearly, therefore, the two Exchange may be responsible for most of the information on SPDR prices.

Consistent with the prior studies (Barclay & Warner, 1993; Chakravarty, 2001), this study defines small-sizes trades as those consisting of 1-499 shares, medium-sized trades as 500-9,999 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 64.89% (26.05%) of small trades, 48.24% (43.56%) of medium-sized trades and 33.90% (43.07%) of block trades in the first period, and the NASDAQ (NYSE-Arca) accounts for 62.52% (23.91%) of small trades, 48.18% (35.61%) of medium-sized trades and 38.23% (36.99%) of block trades in the second period. Although the NASDAQ is the most active in terms of small and medium trades, the NYSE-Arca is the relative active block trades comparing with the NASDAQ in the first period. Therefore 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 in the whole sample period.

< Table 2 Inserted about here>

The number of trades, trade size and transactions by trade size in the E-mini futures on the CME are reported in Table 2. This study defines small-sizes trades as those consisting of 1-4 contracts, medium-sized trades as 5-9 contracts, and large-sized (block) trades as 10 contracts or greater. This table shows that most of all transactions are attributable to the small-size trades. Clearly, therefore, the small-size trades may be responsible for most of the information on E-mini futures prices because of the prevalence of high-frequency trading. The growth in the transactions shows that the demand for hedge purpose had largely increased in the period of credit crunch during 2007.

<Table 3 inserted about here>

The liquidity analysis of SPDRs is reported in Table 3. Table 3 shows that NASDAQ has lowest spread and highest MQI in the first and second periods, indicating that higher liquidity causes a lower market impact cost within the transaction costs as a whole. Accordingly, the study infers that the NASDAQ will lead to the highest contribution to the overall process of price discovery in the S&P 500 ETF market owing to with highest market quality index. This finding that market liquidity of the SPDR shows a decrease pattern in the second period is also consistent with the study of Chiu, Chung, Ho, and Wang (2012), in that the lower market liquidity has been accompanied by the increased funding illiquidity in 2007. Similar finding is also presented in Table 2, indicating a decrease in market liquidity in the E-mini S&P 500 index futures markets.

4.2 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).[14] The trade price is set as the last sale price at the end of the second period. This study also follows 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 five venues (i.e., AMEX, NSX, NASD ADF/TRF, NYSE-Arca and NASDAQ) in the first and second periods. As shown in Table 1, the AMEX, NSX, NASD ADF/TRF, NYSE-Arca and NASDAQ account for over 98% of all transactions and 97% 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; the remaining exchanges, which account for less than 2% of all transactions, are excluded from the analysis. Tse et al. (2006) and Chen

[14] 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.

and Chung (2012) indicate that the ArcaEx ECN accounts for most of the price discovery for SPDRs.

<Table 4 inserted about here>

The results of the examination of price discovery in SPDR trades for these venues are reported in Table 4. The price discovery analyses using the PT, IS and MIS models in the first period are reported in Panel A of Table 4, from which we can see that, the NASDAQ accounts for 47.1% of the price discovery in the PT model, 53.2% in the IS model, and 55.0% in the MIS model, contributions that are much higher than those of any of the other venues. This result in the first period is inconsistent with the findings of Tse et al. (2006) and Chen and Chung (2012), who show the ArcaEx ECN dominates all of the other venues in the price-discovery process of the SPDR.[15] In addition, the price discovery results in the second period are presented in Panel B of Table 4, from which we can see that, the NASDAQ accounts for 47.3% of the price discovery in the PT model, 51.5% in the IS model, and 55.2% 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 lead exchange in price discovery of the SPDR market because the NASDAQ became operational as an exchange in other exchange listed securities as well. These results are consistent with the previous conjecture from the results of Tables 3, that the NASDAQ provides highest contribution to the overall process of price discovery in the SPDR market.

<Table 5 inserted about here>

[15] 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), Tse et al. (2006) and Chen and Chung (2012) show that ArcaEx ECN has proven to be a significant contributor within the overall the process of price discovery.

We also examine price discovery in SPDR quoted midpoints for the five venues. The results are reported in Table 5, indicating that the quote prices on NASDAQ (NSX) provide larger contribution than other venues in the first (second) period. Overall, NASDAQ is clearly the dominant contributor to price discovery within the SPDR markets. These results are consistent with the results of Chung and Chuwonganant (2012) who find the result of NASDAQ offering a faster and higher probability of execution than other trading venues, implying that traders are more likely to send orders to NASDAQ. Overall, the above empirical results suggest that trade prices on NASDAQ should be used to represent SPDR when examining the dynamics of price discovery.

4.3 Price Discovery Analyses in E-mini Futures and SPDRs

Prior studies suggest that E-mini futures contribute the most to price discovery (Chu et al, 1999; Hasbrouck, 2003) and ETFs play a significant role in the price-discovery process (Tse et al, 2006; Chen & Chung, 2012). The price-discovery results for the S&P 500 index, E-mini futures and SPDRs using the PT, IS and MIS models are reported in Table 6. The results of the PT, IS and MIS models indicate that relative to the other markets, SPDRs are quite dominant, with a significant contribution to the price-discovery process in the first and second periods.

<Table 6 inserted about here>

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 the prior studies (Chu et al, 1999; Hasbrouck, 2003; Tse et al, 2006; Chen & Chung, 2012), which argue the E-mini futures playing a dominant role on the price-discovery process, and reemphasizes the significance of the ETF in contributing to price discovery. However, E-mini index futures have more contributions to price discovery in the second period than that in the first period, reflecting that the contribution of SPDRs to price discovery is large suffering from funding illiquidity than that of E-minis.

4.4 Regression Analyses in Market Liquidity of E-minis and SPDRs

The purpose of this paper is to investigate the influences of funding liquidity on market quality. We first observe the change in market liquidity for E-minis and SPDRs before and after the start of the credit crunch.

<Table 7 inserted about here>

Panel A of Table 7 shows the regression analysis for market liquidity of E-minis by measuring spreads (*FSP*) in the first period.[16] In specifications (1) to (7), the results show that the estimated coefficient on market volatility is positive significantly in the liquidity regression model, indicating that higher market risk leads to a reduction in market liquidity. The results are similar to the prior studies (Copeland & Galai, 1983; Amihud & Mendelson, 1987; McInish & Wood, 1992; Chiu et al., 2012) that find that volatility has a positive impact on the spread. In specifications (2) to (7), we find that the impacts of funding liquidity variables on liquidity are inconsistent, reflecting that funding liquidity may be not an important determinant to liquidity of E-minis before the start of the credit crunch. In specifications (1), (3), (5) and (7), the estimated coefficients on SPDRs liquidity (*SSP*) are positive significantly in the E-mini liquidity regression, showing that SPDRs liquidity affects the E-minis liquidity even if we consider the effect of funding liquidity into the regression models.

Similar results are also presented in Panel B of Table 7. Panel B of Table 7

[16] Since there is no quote data of the E-mini S&P 500 index futures in this study, we only estimate spreads from trade prices to proxy market liquidity.

shows the regression analysis for market liquidity of E-minis by measuring spreads (*FSP*) in the second period. In specifications (9), (11) and (13), the estimated coefficients on funding liquidity are all positive significantly, indicating that funding liquidity affects market liquidity of E-minis during the subprime crisis period. In specifications (10), (12) and (14), we simultaneously consider effects of funding liquidity and SPDRs liquidity on E-minis liquidity. However, the effect of funding liquidity will be offset by the influence of SPDRs liquidity, indicating that SPDR liquidity plays an important role of mediator in the relationship between funding liquidity and E-minis liquidity during period of market declines.

<Table 8 inserted about here>

Panel A of Table 8 presents the regression analysis for market liquidity of SPDRs by measuring spreads (*SSP*) in the first period. In specifications (1) to (7), the results show that the estimated coefficient on number of trades is negative significantly and the estimated coefficient on market volatility is positive significantly in the liquidity regression model, indicating that lower trading frequency and higher market risk leads to a reduction in market liquidity. In specifications (2) to (7), we find that the impacts of funding liquidity variables on liquidity are significantly positive, reflecting that funding liquidity is an important determinant to liquidity of SPDRs before the start of the credit crunch. In specifications (1), (3), (5) and (7), the estimated coefficients on E-minis liquidity (FSP) are insignificant in the SPDR liquidity regression, showing that E-minis liquidity does not affect SPDRs liquidity during the normal period.

Panel B of Table 8 presents the regression analysis for market liquidity of SPDRs by measuring spreads (*SSP*) in the second period. In specifications (9), (11) and (13), the estimated coefficients on funding liquidity are all positive significantly, indicating that funding liquidity affects market liquidity of SPDRs during the subprime crisis period. In specifications (10), (12) and (14), we simultaneously consider effects of funding liquidity and E-minis liquidity on SPDRs liquidity. However, the effect of funding liquidity will be offset by the influence of E-minis liquidity, indicating that E-minis liquidity plays an important role of mediator in the relationship between funding liquidity and SPDRs liquidity during period of market declines. Overall, the results present that the spillover effect in the relationship of liquidity between SPDRs and E-minis, supporting the argument of Cespa and Foucault (2014) for comovements in assets' illiquidities.

4.5 Regression Analyses in Price Discovery of E-minis and SPDRs

In order to provide evidence that the contribution to price discovery is affected by a decrease in market liquidity and funding liquidity, details on the relationships that exist between trade price discovery and control variables based on the regression analysis are presented in Table 9.

<Table 9 inserted about here>

Panel A of Table 9 shows the regression analysis for price discovery of SPDRs measured by the common factor (PT), information share (IS) and modified information share (MIS) models for SPDR trades compared with E-mini futures prices in the first period. The coefficients on the spread ratio variable reveal significantly negative explanatory power on the price-discovery measures, suggesting the transaction costs hypothesis helps explain the effect of market liquidity on price discovery. In addition, the coefficients on the *Sigma* variable reveal the significantly negative explanatory power of market volatility on the price discovery measures, which suggest that the leverage effect in the price discovery analysis is strengthened in high volatility periods. Finally, the coefficients on funding illiquidity (*FundLiq*) are found to be insignificant explanatory power, indicating that the influence of funding liquidity on the contributions of E-mini index futures and SPDRs to price discovery is mixed in the normal period.

Panel B of Table 9 shows the regression analysis for price discovery of SPDRs measured by the common factor (PT), information share (IS) and modified information share (MIS) models for SPDR trades compared with E-mini futures prices in the second period. The coefficients on the *Sigma* variable still reveal the significantly negative explanatory power of market volatility on the price discovery measures. However, the coefficients on the spread ratio and funding illiquidity variables reveal insignificant explanatory power on the price discovery measures. Such results imply that liquidity does not affect price discovery during the subprime crisis period, inferring that the liquidity spillover between SPDRs and E-minis causes a mixed effect on price discovery.

Overall, the regression results are shown in Table 9, which depicts that all of the coefficients on the funding illiquidity variable are insignificantly negative or positive, indicating that it is not clear for the overall influence of funding illiquidity on price discovery because of the liquidity spillovers between SPDRs and E-minis. However, we find that market volatility is an important determinant on the price discovery process.

5. CONCLUSIONS

This study analyzes the changes of market quality before and after the period of credit crunch in 2007 by examining the impact of funding liquidity on market liquidity and price discovery of S&P 500 ETFs and E-mini index futures. The dynamics of market liquidity and price discovery between the S&P 500 index, ETFs and E-mini index futures have examined. The empirical results show that funding illiquidity affects market liquidity of SPDRs and E-minis. With an increase in funding illiquidity during the subprime crisis period, there is a significant liquidity spillover between SPDRs and E-minis. This result is consistent with the argument of Cespa and Foucault (2014). The empirical results also show that the SPDR appear to significantly lead the E-mini futures in the price-discovery process, reflecting the importance of the SPDR in the price-discovery process in the S&P 500 index market.

Although the contribution of E-mini index futures to price discovery is small less than that of SPDRs, we show that E-minis with leverage characteristic still play an important role in the price-discovery process during the high volatility period. In addition, we find the influence of funding illiquidity on the contribution of E-mini index futures to price discovery is higher that of SPDRs. However, considering the effects of other market factors on the contribution to price discovery, the empirical results suggest that changes in contribution of SPDRs and E-minis are mixed because of the liquidity spillover effects. Overall, the findings show the important influence of funding liquidity on market liquidity and price discovery for SPDRs and the E-mini index futures.

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

Trading Centers	Number of Trades (%)	Trade Volume (100 shares) (%)	Avg. Size Per Trade (100 shares)	Transactions by Size (shares) Small Size (%)	Medium Size (%)	Large Size (%)
Panel A: First Period (12 February 2007-9 August 2007, 125 trading days)						
A (AMEX)	(1.10%)	(1.45%)	9.77	(1.21%)	(0.95%)	(2.24%)
B (Boston)	(0.08%)	(0.03%)	2.52	(0.13%)	(0.02%)	(0.00%)
C (NSX)	(0.88%)	(0.81%)	6.83	(0.93%)	(0.82%)	(0.77%)
D (NASD ADF/TRF)	(5.72%)	(19.13%)	24.84	(5.65%)	(5.71%)	(16.07%)
I (ISE)	(0.42%)	(0.31%)	5.47	(0.54%)	(0.28%)	(0.07%)
M (Chicago)	(0.01%)	(0.65%)	768.44	(0.00%)	(0.00%)	(0.69%)
N (NYSE)	(0.41%)	(0.42%)	7.54	(0.51%)	(0.29%)	(0.68%)
P (NYSE-Arca)	(33.77%)	(36.11%)	7.94	(26.05%)	(43.56%)	(43.07%)
T (NASDAQ)	(57.48%)	(40.57%)	5.24	(64.89%)	(48.24%)	(33.90%)
W (CBOE)	(0.12%)	(0.50%)	30.54	(0.10%)	(0.13%)	(2.48%)
X (Philadelphia)	(0.00%)	(0.02%)	841.08	(0.00%)	(0.00%)	(0.02%)
Total	21,837,263	162,224,383	7.43	12,210,540	9,524,829	101,894
Panel B: Second Period (10 August 2007-31 December 2007, 99 trading days)						
A (AMEX)	(1.58%)	(1.73%)	7.23	(1.71%)	(1.39%)	(2.98%)
B (Boston)	(0.00%)	(0.00%)	4.03	(0.01%)	(0.00%)	(0.00%)
C (NSX)	(0.80%)	(0.74%)	6.11	(0.80%)	(0.80%)	(0.70%)
D (NASD ADF/TRF)	(11.04%)	(22.00%)	13.21	(9.72%)	(12.93%)	(16.36%)
I (ISE)	(1.04%)	(0.85%)	5.43	(1.13%)	(0.91%)	(0.46%)
M (Chicago)	(0.08%)	(0.73%)	58.34	(0.10%)	(0.04%)	(1.19%)
N (NYSE)	(0.02%)	(0.03%)	9.80	(0.02%)	(0.02%)	(0.08%)
P (NYSE-Arca)	(28.68%)	(30.98%)	7.16	(23.91%)	(35.61%)	(36.99%)
T (NASDAQ)	(56.64%)	(42.18%)	4.94	(62.52%)	(48.18%)	(38.23%)
W (CBOE)	(0.10%)	(0.69%)	46.96	(0.07%)	(0.12%)	(2.93%)
X (Philadelphia)	(0.01%)	(0.08%)	62.32	(0.01%)	(0.00%)	(0.06%)
Total	26,061,292	172,785,767	6.63	15,454,340	10,507,858	99,094

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 size per trade, and transactions by trade size (small, medium, and large) in different trading centers for SPDRs. This study defines small-sizes trades as those consisting of 1-499 shares, medium-sized trades as 500-9,999 shares, and large-sized (block) trades as 10,000 shares or greater.

Table 2 Number of Transactions and Trading Volume for E-mini S&P500 Index Futures in CME

Number of Trades	Trade Volume	Quoted Spread	Avg. Size Per Trade	Transactions by Size (contracts) Small Size	Medium Size	Large Size
Panel A: First Period (12 February 2007-9 August 2007, 125 trading days)						
9,993,501	153,740,437	0.0174%	15.38	6,266,865	3,404,380	322,256
Panel B: Second Period (10 August 2007-31 December 2007, 99 trading days)						
12,853,444	149,568,596	0.0177%	11.64	8,750,284	3,819,363	283,797

Note. This table presents the transactions and trading volumes of E-mini S&P 500 index futures on CME. This table reports the total number of trades, total trade size, quoted spread, average size per trade, and transactions by trade size (small, medium, and large) on CME. This study defines small-sizes trades as those consisting of 1-4 contracts, medium-sized trades as 5-9 contracts, and large-sized (block) trades as 10 contracts or greater. We computed quoted bid-ask spreads by implementing the methodology suggested in Wang et al. (1994).

Table 3 Summary Statistics of SPDRs

Trading Centers	Number of Quotes (%)	Quoted Depth (100 shares)	Quoted Spread	Market Quality Index (*MQI*)
Panel A: First Period (12 February 2007-9 August 2007, 125 trading days)				
A (AMEX)	(2.90%)	145.35	0.0344%	27.27
B (Boston)	(0.00%)	12.32	0.4376%	0.32
C (NSX)	(21.49%)	420.67	0.0127%	160.71
D (NASD ADF/TRF)	(3.14%)	194.61	0.0488%	35.03
I (ISE)	(10.59%)	70.27	0.0277%	19.83
M (Chicago)	(0.00%)	10.25	0.1270%	0.54
N (NYSE)	(1.86%)	51.53	0.0719%	4.72
P (NYSE-Arca)	(19.80%)	590.65	0.0091%	318.42
T (NASDAQ)	(38.55%)	575.08	0.0086%	328.53
W (CBOE)	(1.67%)	317.80	0.3034%	29.96
X (Philadelphia)	(0.00%)	2.00	0.0139%	0.72
Overall	81,671,193	453.03	0.0198%	228.79
Panel B: Second Period (10 August 2007-31 December 2007, 99 trading days)				
A (AMEX)	(5.53%)	80.90	0.0338%	12.70
B (Boston)	(0.00%)	97.85	0.3304%	5.41
C (NSX)	(14.88%)	135.79	0.0172%	50.28
D (NASD ADF/TRF)	(3.85%)	65.15	0.0461%	9.28
I (ISE)	(14.70%)	174.90	0.0166%	73.34
M (Chicago)	(1.69%)	503.59	0.0518%	50.01
N (NYSE)	(0.07%)	102.82	0.1183%	4.62
P (NYSE-Arca)	(18.55%)	209.04	0.0098%	112.93
T (NASDAQ)	(38.82%)	251.85	0.0091%	143.09
W (CBOE)	(1.79%)	376.88	0.3618%	18.55
X (Philadelphia)	(0.12%)	2.02	0.0277%	0.38
Overall	97,493,120	204.80	0.0215%	97.00

Note: This table presents the quoted prices and sizes 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). The quoted depth (*Depth*) is calculated as ($Q_{bid} + Q_{ask}$) and the quoted spread (*SP*) is calculated as [($P_{ask} - P_{bid}$) / P_{mid}], and the market quality index (*MQI*) is calculated as [*Depth*/2/100] / [*SP*×100], where Q_{ask} is the depth at ask, Q_{bid} is the depth at bid, P_{ask} is the ask price, P_{bid} is the bid price, and P_{mid} is the midpoint of the bid and ask prices of the quotes. *** indicates that the difference for the traditional t-test is significant at the 1% level.

Table 4 Trade Price Discovery Analysis in the SPDR Market

	AMEX	NSX	NASD ADF/TRF	NYSE-Arca	NASDAQ
Panel A: First Period (12 February 2007-9 August 2007, 114 trading days)					
PT Model	0.079	0.116	0.043	0.291	0.471
IS Model	0.021	0.045	0.035	0.367	0.532
MIS Model	0.021	0.044	0.033	0.353	0.550
Panel B: Second Period (10 August 2007-31 December 2007, 99 trading days)					
PT Model	0.080	0.204	0.039	0.204	0.473
IS Model	0.027	0.136	0.041	0.282	0.515
MIS Model	0.026	0.135	0.033	0.255	0.552

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, NSX, NASD ADF/TRF, NYSE-Arca 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 February 12, 2007 to December 31, 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 Quote Price Discovery Analysis of Prices in the SPDR Market

	AMEX	NSX	NASD ADF/TRF	NYSE-Arca	NASDAQ
Panel A: First Period (12 February 2007-9 August 2007, 114 trading days)					
PT Model	0.107	0.260	0.094	0.192	0.347
IS Model	0.088	0.232	0.120	0.209	0.351
MIS Model	0.068	0.237	0.118	0.197	0.380
Panel B: Second Period (10 August 2007-31 December 2007, 92 trading days)					
PT Model	0.129	0.320	0.068	0.195	0.288
IS Model	0.152	0.292	0.094	0.217	0.245
MIS Model	0.139	0.292	0.091	0.199	0.279

Note: The results for price discovery of quote midpoint 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 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 February 12, 2007 to December 31, 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 6 Price Discovery Analysis in S&P 500 index, E-mini Futures and SPDRs Markets

	SPDRs	E-mini Futures	S&P 500 Index
Panel A: First Period (12 February 2007-9 August 2007, 124 trading days)			
PT Model	0.578	0.253	0.169
IS Model	0.538	0.413	0.049
MIS Model	0.539	0.412	0.049
Panel B: Second Period (10 August 2007-31 December 2007, 98 trading days)			
PT Model	0.533	0.311	0.156
IS Model	0.486	0.464	0.050
MIS Model	0.485	0.465	0.050

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 and SPDRs. 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 February 12, 2007 to December 31, 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 7 Regression analyses of market liquidity for E-mini S&P 500 Index Futures

	Panel A: First Period (12 February 2007-9 August 2007, 124 trading days)							Panel B: Second Period (10 August 2007-31 December 2007, 98 trading days)						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Constant	1.618***	1.988***	1.696***	1.975***	1.699***	1.270***	1.007***	0.991***	0.897**	0.917***	1.052**	0.967***	1.090***	0.985***
	(6.974)	(7.107)	(6.326)	(8.094)	(7.187)	(4.020)	(4.176)	(4.729)	(2.150)	(4.330)	(2.451)	(4.826)	(2.630)	(4.601)
$\log(FNT)$	-0.017	-0.033	-0.024	-0.033	-0.026	0.042	0.050**	-0.009	0.058	0.001	0.045	-0.006	0.044	-0.001
	-(0.767)	-(1.203)	-(0.949)	-(1.380)	-(1.171)	(1.325)	(2.066)	-(0.464)	(1.572)	(0.047)	(1.169)	-(0.337)	(1.170)	-(0.056)
FSig	0.119***	0.174***	0.119***	0.171***	0.117***	0.141***	0.093***	0.073**	0.151***	0.080**	0.161***	0.080**	0.163***	0.089***
	(3.820)	(5.071)	(3.747)	(4.920)	(3.672)	(5.149)	(3.458)	(2.345)	(3.827)	(2.370)	(4.143)	(2.337)	(3.907)	(2.870)
FRet	0.016*	0.016*	0.016*	0.017*	0.017*	0.017*	0.017**	0.011	0.018	0.012	0.017	0.012	0.018	0.013*
	(1.782)	(1.717)	(1.822)	(1.878)	(1.938)	(1.963)	(2.077)	(1.448)	(1.569)	(1.547)	(1.531)	(1.528)	(1.498)	(1.724)
SSP	0.287***		0.279***		0.290***		0.261***	0.916***		0.838***		0.875***		0.792***
	(4.130)		(3.610)		(3.890)		(5.076)	(6.411)		(5.247)		(5.535)		(5.419)
ABCP		0.146	0.124						0.067***	0.026				
		(0.580)	(0.607)						(2.658)	(1.351)				
LIBOR				0.312*	0.260*						0.092*	0.036		
				(1.965)	(1.959)						(1.794)	(0.828)		
REPO						-0.840**	-1.002***						0.074***	0.036**
						-(2.399)	-(3.301)						(3.007)	(2.561)
Adj. R^2	0.436	0.390	0.437	0.397	0.444	0.480	0.542	0.792	0.540	0.789	0.519	0.792	0.537	0.786

Note: The changes in market liquidity of index futures are tested based on the following regression model (Equation 10):

$$FSP_t = \beta_0 + \beta_1 \log(FNT_t) + \beta_2 FSig_t + \beta_3 FRet_t + \beta_4 SSP_t + \beta_5 FundLiq_t + \varepsilon_t \tag{10}$$

where t indicates the daily time interval; FSP_t refers to the daily market liquidity for S&P 500 index futures measured by the spread during trading day t; SSP_t refers to the daily market liquidity for index futures measured by spread during trading day t; FNT_t is the number of trades for index futures during trading day t; $FSig_t$ is the Parkinson (1980) extreme value estimator which proxies for the volatility of index futures during trading day t; $FRet_t$ is the market return for index futures during trading day t; and $FundLiq_t$ is the funding liquidity measure, including Libor, ABCP and Repo, during trading day t. The regression models are estimated using the generalized method of moment (GMM) approach, which uses the lagged spread and lagged volatility as the instrumental variables for the spread of SPDRs. Standard errors and covariance are computed using Newey-West robust standard error estimators. 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 8 Regression analyses of market liquidity for SPDRs

	Panel A: First Period (12 February 2007-9 August 2007, 124 trading days)							Panel B: Second Period (10 August 2007-31 December 2007, 98 trading days)						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Constant	1.229*	2.098***	1.828***	1.873***	1.435**	2.410***	1.646***	-0.483	0.084	-0.570*	0.232	-0.600*	0.286	-0.992
	(1.899)	(3.618)	(2.740)	(3.158)	(2.127)	(4.521)	(3.117)	-(1.633)	(0.282)	-(1.774)	(0.728)	-(1.865)	(1.004)	-(1.282)
$\log(SNT)$	-0.034	-0.126**	-0.073	-0.107*	-0.046	-0.160***	-0.110**	0.003	0.059**	0.003	0.047*	0.006	0.043*	-0.005
	-(0.698)	-(2.335)	-(1.528)	-(1.940)	-(0.947)	-(3.239)	-(2.368)	(0.285)	(2.278)	(0.187)	(1.684)	(0.470)	(1.710)	-(0.258)
SSig	0.176***	0.252***	0.170***	0.260***	0.174***	0.276***	0.146***	-0.002	0.079***	-0.020	0.089***	-0.021	0.092***	-0.082
	(3.453)	(2.961)	(3.036)	(3.155)	(3.277)	(3.277)	(2.884)	-(0.043)	(3.359)	-(0.342)	(3.711)	-(0.376)	(4.128)	-(0.694)
SRet	0.003	0.003	0.003	0.005	0.005	0.000	-0.008	-0.001	-0.001	-0.004	-0.001	-0.004	-0.001	-0.013
	(0.294)	(0.272)	(0.255)	(0.440)	(0.537)	-(0.034)	-(0.788)	-(0.132)	-(0.101)	-(0.338)	-(0.134)	-(0.384)	-(0.092)	-(0.685)
FSP	-0.067		-0.179		-0.130		0.130	0.758***		0.823***		0.819***		1.151**
	-(0.213)		-(0.580)		-(0.404)		(0.457)	(4.252)		(3.176)		(3.771)		(2.156)
ABCP		0.676**	0.848***						0.049**	-0.011				
		(2.270)	(2.718)						(2.275)	-(0.427)				
LIBOR				0.368***	0.483**						0.059	-0.008		
				(2.645)	(2.233)						(1.426)	-(0.182)		
REPO						0.984***	1.312***						0.049*	-0.038
						(2.956)	(5.288)						(1.976)	-(1.015)
Adj. R^2	0.252	0.360	0.239	0.333	0.233	0.391	0.355	0.706	0.477	0.687	0.451	0.688	0.468	0.444

Note: The changes in market liquidity of SPDRs are tested based on the following regression model (Equation 11):

$$SSP_t = \beta_0 + \beta_1 \log(SNT_t) + \beta_2 SSig_t + \beta_3 SRet_t + \beta_4 FSP_t + \beta_5 FundLiq_t + \varepsilon_t \tag{11}$$

where t indicates the daily time interval; SSP_t refers to the daily market liquidity for index futures measured by spread during trading day t; FSP_t refers to the daily market liquidity for S&P 500 index futures measured by the spread during trading day t; SNT_t is the number of trades for SPDRs during trading day t; $SSig_t$ is the Parkinson (1980) extreme value estimator which proxies for the volatility of SPDRs; $SRet_t$ is the market return for SPDRs during trading day t; and $FundLiq_t$ is the funding liquidity measure, including Libor, ABCP and Repo, during trading day t. The regression models are estimated using the generalized method of moment (GMM) approach, which uses the lagged spread and lagged volatility as the instrumental variables for the spread of E-minis. Standard errors and covariance are computed using Newey-West robust standard error estimators. 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 9 Regression analyses of price discovery for SPDRs and E-minis

	PT Model				IS Model				MIS Model			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: First Period (12 February 2007-9 August 2007, 124 trading days)												
Constant	-0.988 -(0.903)	-1.478 -(1.077)	-1.471 -(1.174)	-1.915 -(1.048)	-1.443 -(1.066)	-2.531* -(1.756)	-2.305* -(1.712)	-3.722** -(1.991)	-1.050 -(0.712)	-2.258 -(1.505)	-2.005 -(1.415)	-3.581* -(1.877)
$\log\left(\frac{SVol}{FVol}\right)$	-0.184 -(0.350)	-0.425 -(0.657)	-0.327 -(0.585)	-0.451 -(0.656)	0.095 (0.147)	-0.439 -(0.664)	-0.159 -(0.257)	-0.560 -(0.775)	0.387 (0.522)	-0.207 -(0.297)	0.105 (0.153)	-0.341 -(0.456)
$\log\left(\frac{SNT}{FNT}\right)$	0.903 (1.071)	0.977 (1.123)	0.955 (1.125)	0.842 (1.016)	1.173 (1.286)	1.335 (1.428)	1.265 (1.383)	1.021 (1.066)	0.897 (0.943)	1.078 (1.106)	0.999 (1.051)	0.729 (0.714)
$\log\left(\frac{SSP}{FSP}\right)$	-2.939** -(2.277)	-3.171** -(2.360)	-2.988** -(2.339)	-3.519** -(2.194)	-3.050* -(1.828)	-3.564** -(2.101)	-3.137* -(1.921)	-4.475** -(2.279)	-3.214* -(1.846)	-3.786** -(2.125)	-3.311* -(1.940)	-4.797** -(2.315)
Sigma	-0.998** -(2.136)	-1.163** -(2.340)	-1.191** -(2.311)	-1.075** -(2.248)	-1.118* -(1.693)	-1.484* -(1.918)	-1.462* -(1.934)	-1.307* -(1.871)	-1.427* -(1.727)	-1.833* -(1.900)	-1.807* -(1.921)	-1.636* -(1.872)
ABCP		3.705 (0.767)				8.223* (1.734)				9.137 (1.617)		
LIBOR			4.949 (0.971)				8.820** (1.996)				9.780* (1.836)	
REPO				3.373 (0.787)				8.288 (1.495)				9.205 (1.465)
Adj. R^2	0.220	0.221	0.223	0.219	0.222	0.243	0.240	0.241	0.226	0.248	0.244	0.245

Table 9 Regression analyses of price discovery for SPDRs and E-minis (Contd.)

	PT Model				IS Model				MIS Model			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel B: Second Period (10 August 2007-31 December 2007, 98 trading days)												
Constant	0.918 (0.268)	0.564 (0.160)	0.847 (0.241)	0.887 (0.257)	0.429 (0.109)	0.019 (0.005)	0.383 (0.095)	0.469 (0.119)	0.389 (0.088)	-0.077 -(0.017)	0.340 (0.075)	0.461 (0.104)
$\log\left(\frac{SVol}{FVol}\right)$	-0.753 -(0.707)	-1.344 -(1.145)	-0.793 -(0.714)	-0.780 -(0.694)	0.018 (0.014)	-0.664 -(0.519)	-0.007 -(0.006)	0.052 (0.041)	0.494 (0.326)	-0.281 -(0.176)	0.467 (0.297)	0.554 (0.345)
$\log\left(\frac{SNT}{FNT}\right)$	0.339 (0.270)	1.058 (0.841)	0.399 (0.309)	0.357 (0.284)	0.257 (0.164)	1.087 (0.738)	0.295 (0.186)	0.234 (0.150)	0.168 (0.092)	1.112 (0.670)	0.209 (0.114)	0.127 (0.070)
$\log\left(\frac{SSP}{FSP}\right)$	0.372 (0.071)	1.492 (0.267)	0.476 (0.089)	0.390 (0.074)	-0.587 -(0.096)	0.706 (0.109)	-0.521 -(0.084)	-0.610 -(0.099)	-1.519 -(0.222)	-0.050 -(0.007)	-1.450 -(0.210)	-1.560 -(0.227)
Sigma	-0.779* -(1.865)	-0.807* -(1.962)	-0.783* -(1.868)	-0.777* -(1.849)	-0.958** -(2.118)	-0.990** -(2.190)	-0.961** -(2.114)	-0.960** -(2.109)	-1.289** -(2.272)	-1.325** -(2.349)	-1.291** -(2.273)	-1.292** -(2.252)
ABCP		0.604 (1.441)				0.697 (1.422)				0.792 (1.368)		
LIBOR			0.155 (0.201)				0.099 (0.112)				0.105 (0.103)	
REPO				0.044 (0.129)				-0.056 -(0.142)				-0.100 -(0.199)
Adj. R^2	0.047	0.062	0.037	0.037	0.041	0.056	0.031	0.031	0.055	0.066	0.045	0.045

Note: The changes in the contribution of SPDRs to price discovery relative to E-mini index futures are tested based on the following regression model (Equation 12):

$$\log\left(\frac{PD}{1-PD}\right)_t = \beta_0 + \beta_1 \log\left(\frac{SVol}{FVol}\right)_t + \beta_2 \log\left(\frac{SNT}{FNT}\right)_t + \beta_3 \log\left(\frac{SSP}{FSP}\right)_t + \beta_4 Sigma_t + \beta_5 FundLiq_t + \varepsilon_t \tag{12}$$

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 compared with E-mini futures prices during trading day t; $SVol_t$ ($FVol_t$) is the trade volume for SPDRs (E-minis) during trading day t; SNT_t (FNT_t) is the number of trades for SPDRs (E-minis) during trading day t; SSP_t (FSP_t) refers to the daily market liquidity for SPDRs (E-minis) measured by the spread during trading day t; $Sigma_t$ is the Parkinson (1980) extreme value estimator which proxies for the volatility of the S&P 500 index market on trading day t; and $FundLiq_t$ is the funding liquidity measure, including Libor, ABCP and Repo, in trading day t. 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.

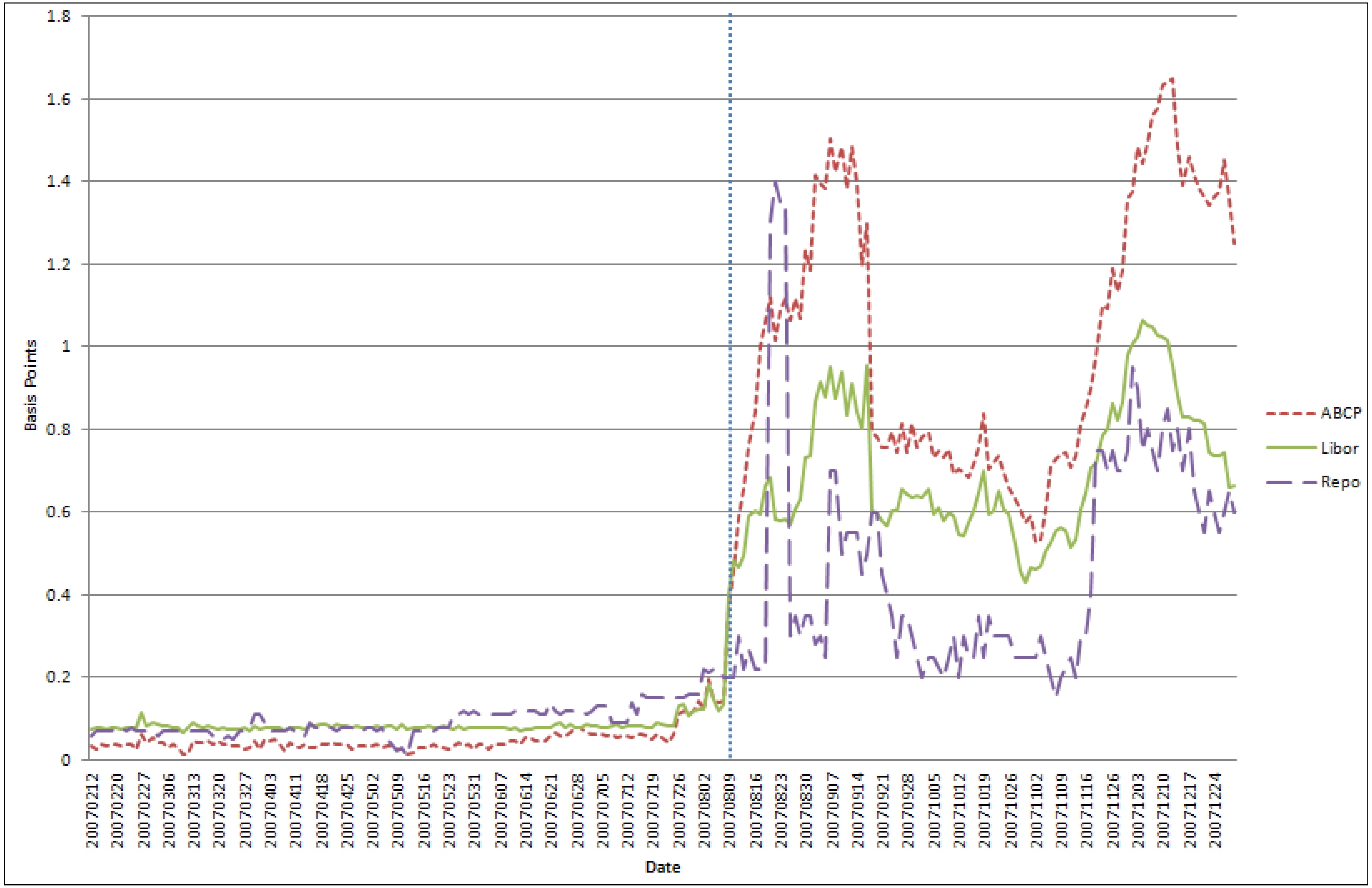

Figure 1 Measures of Funding Liquidity

Note This figure plots the time-series daily value of Libor, ABCP and Repo during the period from 12 February 2007 to 31 December 2007. The ABCP is measured by the spread between the three-month ABCP rate and the overnight index swap; the Libor is measured by the spread between the U.S. three-month inter-bank labor rate and the overnight index swap; and the Repo is calculated as the mortgage repossession rate minus the government repossession rate.

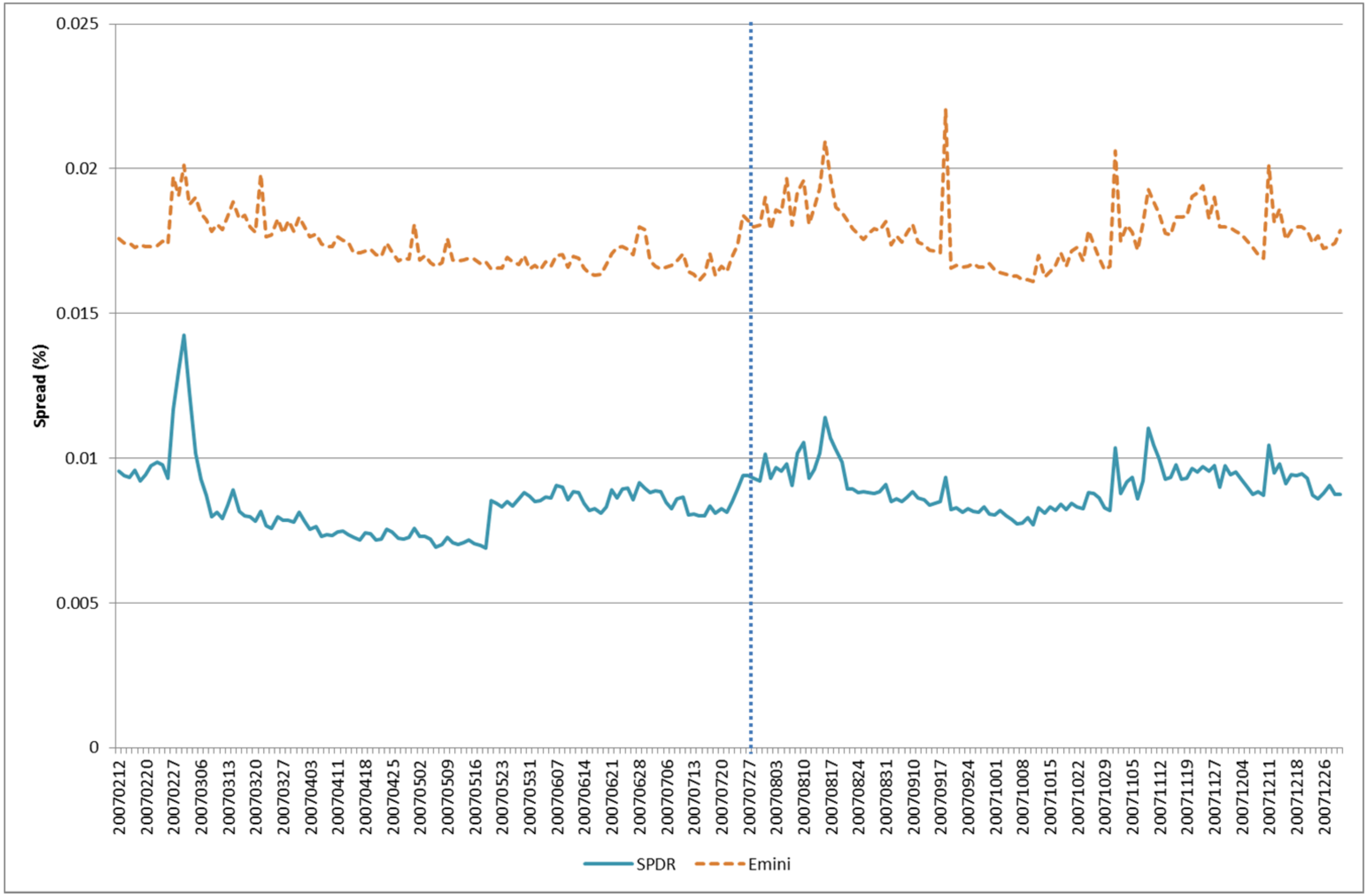

Figure 2 Percentage Spreads of SPDRs and S&P 500 E-mini Index Futures