ARTICLE IN PRESS

North American Journal of Economics and Finance xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

North American Journal of Economics and Finance

journal homepage: www.elsevier.com/locate/najef

The impact of funding liquidity on market quality

Wei-Peng Chen[a], Shu Ling Lin[a], Jun Lu[b], Chih-Chiang Wu[c,*]

[a] Department of Information and Finance Management at the National Taipei University of Technology, Taipei, Taiwan
[b] Department of Business Management at the National Taipei University of Technology, Taipei, Taiwan
[c] Discipline of Finance at College of Management at Yuan Ze University, Taoyuan, Taiwan

ARTICLE INFO

JEL classification:
G13
G20
C32

Keywords:
Funding liquidity
Market quality
Price discovery
Market liquidity
Spillover

ABSTRACT

This study analyzes market quality during the 2007–2008 credit crunch, by examining the impact of funding liquidity on market liquidity and price discovery of S&P 500 exchange-traded funds (i.e., S&P 500 depositary receipts [SPYs]) and index futures (E-minis). The empirical results show that funding liquidity affects market liquidity, and that the impact of illiquidity contagion between SPYs and E-minis was significant during the subprime mortgage crisis. In particular, the contagion effects between the two markets mediate the impact of funding illiquidity on market liquidity during the credit crunch. Considering the influences of other market factors on price discovery, we suggest that E-mini index futures made less contributions to price discovery during the credit crunch compared to normal periods. The empirical finding emphasizes the importance of the contagion effect between ETF and E-mini futures markets, when they suffer from external shocks.

1. Introduction

The financial crisis that resulted from the subprime mortgage crisis of 2007 was associated with several shocks that underscored the importance of funding liquidity for market quality. During the financial crisis, especially with specific bankruptcy events, the liquidating and hedging needs of short positions emerged because of concerns relating to unscheduled trading halts and uncertainties with clearinghouse integrity. Market professionals recognize their short strategies for reducing equity exposure, thereby exacerbating market fluctuations. The amplification of volatility therefore results in incomplete protection to meet the considerable needs of insurance and liquidation spirals, and this leads to increased capital and margin requirements of investors. As mentioned in Brunnermeier and Pedersen (2009), market liquidity and funding liquidity are mutually reinforcing, and further leading to liquidity spirals.

This study analyzes changes in market quality during the 2007–2008 credit crunch by examining the impact of funding illiquidity on market liquidity and the price discovery of S&P 500 exchange-traded funds ([ETFs]; i.e., S&P 500 depositary receipts [SPYs]) and E-mini index futures (E-minis). As noted in O'Hara (2003), two of the most important functions of the financial markets are price discovery and liquidity. Much of the available empirical literature has examined funding liquidity during the 2008 financial crisis by focusing on equity liquidity, volatility, and resiliency. However, to date no relevant study has considered the impact of funding liquidity on price discovery and the influence of spillovers on market liquidity. To fill this gap, we examine the impact of funding liquidity on changes in market quality in the SPY and E-minis markets that have the characteristics of high liquidity, and discuss the liquidity linkage and illiquidity contagion between the two markets.

Stressed markets produce more cash/futures arbitrage opportunities compared to non-stressed markets (Cheng & White, 2003).

* Corresponding author at: Discipline of Finance, College of Management, Yuan Ze University, 135 Yuan-Tung Road, Chungli, Taoyuan 320, Taiwan.
E-mail address: chihchiang@saturn.yzu.edu.tw (C.-C. Wu).

https://doi.org/10.1016/j.najef.2017.12.002
Received 26 September 2017; Received in revised form 16 December 2017; Accepted 20 December 2017
1062-9408/

Margin requirements increase in illiquidity when margin-setting financiers are unsure whether price changes are triggered by fundamentals news or liquidity shocks (Brunnermeier, 2009). Grossman and Miller (1988) argue that both spot and futures stock markets were highly illiquid on October 19, 1987 (i.e., the day of the crash). Such uncertainty occurs particularly when liquidation pressure leads to price volatility, which in turn raises a financier's expectations regarding future volatility, thus resulting in increased margins. During the market disruptions of 2007, broker-dealer financing and liquidity arrangements drew increasing attention from analysts. Credit ratings agencies recognized these market pressures, noting that major U.S. broker-dealers were liquidity-challenged in the third quarter of 2007, when disruptions in the U.S. subprime period and the spillover into other markets contributed to an overall and widespread market correction.[1]

The issues of liquidity comovement and spillover have received considerable attention and discussion through the development of theoretical models (Brunnermeier & Pedersen, 2009; Cespa & Foucault, 2014; Goldstein, Li, & Yang, 2014).[2] In addition to theoretical works, empirical studies have found that market declines cause asset illiquidity, and binding capital constraints leads to sudden liquidity dry-ups. Hameed, Kang, and Viswanathan (2010) report that negative market returns reduce stock liquidity, especially during periods of tightness in the funding market. Goyenko and Ukhov (2009) note that bond illiquidity acts as an important channel for the transmission of monetary shocks into the stock market, and show that a change in the illiquidity of one market affects illiquidity conditions in the other. Chiu, Chung, Ho, and Wang (2012) demonstrate that a higher degree of funding illiquidity leads to a decline in market liquidity in the ETF market, especially for financial ETFs compared to index ETFs. However, the funding of traders dramatically affects—and is also markedly affected by—market liquidity. Based on the associations between funding and market liquidity, Brunnermeier and Pedersen (2009) develop a theoretical model to link an asset's market illiquidity and risk premium to its funding use and the general shadow cost of funding by analyzing the characteristics of market liquidity.[3] Therefore, the contagion effect between ETFs and index futures could influence the impact of market illiquidity on the market quality of the two markets.

Previous studies that have analyzed the relationship between funding liquidity and market liquidity have also offered recommendations for future research. First, Hameed et al. (2010) indicate that future researchers could investigate the effects of funding constraints by using high-frequency data, because their own evidence is indirect.[4] Second, Cespa and Foucault (2014) recommend that future researchers examine the strength and influence of liquidity spillovers across asset classes. Third, Goldstein et al. (2014) provide an example using index futures markets to show that individual traders are more likely to concentrate on stock index trading, whereas hedge fund trading is more likely to involve index arbitrage, with trading in both equity and index futures markets. Integrating these research recommendations, the current study investigates the impact of funding illiquidity on changes to market quality in SPY and E-mini index futures markets.

Although many studies (Brunnermeier & Pedersen, 2009; Kyle & Xiong, 2001) argue that funding liquidity (i.e., capital constraints) shocks and wealth effects for liquidity supplier are the possible sources of covariation in liquidity supply. Theories of liquidity comovements due to dealers' capital constraints assume that marginal liquidity providers are identical across assets. Cespa and Foucault (2014) argue that this assumption is less tenable across heterogeneous asset classes, suggesting that liquidity providers in one asset class (e.g., ETFs) often learn information from other asset price (e.g., from the underlying assets of ETFs).

Ben-David, Franzoni, and Moussawi (2012, 2014) argue that ETFs impact the liquidity of underlying portfolio, especially during events of market stress. Since the E-mini futures play an important role on hedge trading in the financial markets during the high volatility period. In addition, Ben-David, Franzoni, and Moussawi (2012) indicate that ETFs contributed to shock propagation between the futures market and the equity market during the Flash Crash on May 6, 2010. Based on the concept provided by Cespa and Foucault (2014), authorized participants (APs) and arbitrageurs maybe refer to the information of the index futures to keep ETF prices in line with those of the basket that they aim to track. Furthermore, market makers (or liquidity providers) of the index futures learn the information from the prices of those underlying securities. Illiquidity spillover and contagion between ETFs and index futures are important for market participants, especially during event of market stress such as the 2007–2008 credit crunch. Ben-David, Franzoni, and Moussawi (2017) suggest that ETFs could potentially improve price discovery at the index level. They argue that trading activity from authorized participants (APs) and arbitrageurs helps transmit systematic information from the ETF to the underlying securities and provides liquidity to the underlying securities. APs and arbitrageurs play an important role in the improvement in price discovery and the additional liquidity that ETFs add can enhance price discovery.

Consistent with Brunnermeier and Pedersen (2009) and Chiu et al. (2012), we show that funding liquidity has a significant effect

[1] Furthermore, the "Flash Crash" of May 6, 2010, represents one of the most dramatic events in the history of financial markets. A report from the Commodities Future Trading Commission and the Securities and Exchange Commission identifies one source of the flash crash as index arbitrageurs who opportunistically buy E-minis and simultaneously sell products such as SPYs or individual equities in the S&P 500, which transferred the selling pressure in the futures market to equities markets.

[2] Brunnermeier and Pedersen (2009) provide a model that links an asset's market liquidity and traders' funding liquidity, thereby 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 occur in a dual-asset framework when dealers specialized in different assets learn from others' prices. They report a self-reinforcing, positive relationship between the illiquidity of the two assets. Furthermore, Goldstein et al. (2014) use a similar setting to Cespa and Foucault (2014) to analyze a model in which traders have different trading opportunities and learn information from prices, thereby showing that the diversity of trading motives (speculation or hedging) may reduce price informativeness and increase capital cost.

[3] Brunnermeier and Pedersen (2009) devise a model to demonstrate that market liquidity (a) can suddenly dry up; (b) has commonality across securities; (c) is related to volatility; (d) is subject to "flight to quality"; and (e) co-moves with the market.

[4] Hameed et al. (2010) investigate the impact of market declines on various dimensions of liquidity, including (a) time-series as well as cross-sectional variations in liquidity; (b) commonality in liquidity; and (c) the cost of liquidity provision. Consistent with the results of the previous theoretical model, their results suggest that market liquidity drops after large negative market returns, because the aggregate collateral of financial intermediaries falls and many asset holders are forced to liquidity, making it difficult to provide liquidity precisely when the market requires it.

on the market liquidity of SPYs and E-minis. We also demonstrate that a significant illiquidity contagion existed between SPYs and E-minis during the 2007–2008 credit crunch. In particular, we find that the spillover effect mediated the impact of funding illiquidity on market liquidity during the credit crunch. Although prior studies argue that E-mini index futures dominate the price-discovery process (Chen & Chung, 2012; Chu, Hsieh, & Tse, 1999; Hasbrouck, 2003; Tse, Bandyopadhyay, & Shen, 2006), our empirical results show that SPYs dominated the price-discovery process in S&P 500 index markets during the sample period. In addition, we find that funding illiquidity has a greater influence on the contribution of E-mini index futures to price discovery compared to SPYs. 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 made less contributions to price discovery during the credit crunch compared to normal periods. As noted in Brunnermeier (2009), traders tend not to carry much excess capital and increasing margins during a higher funding illiquidity period, and haircuts force traders to de-leverage their position. Based on these results, we emphasize that the liquidity spillover mediate the importance of funding illiquidity in affecting market liquidity, implying that the influence of contagion effect between SPY and E-mini futures markets may be higher than external shocks.

The remainder of this paper is organized as follows: Section 2 presents a discussion on the data and research methodology adopted for our study; Section 3 provides the empirical results of our research; and lastly, Section 4 offers a conclusion based on our results.

2. Data and research methodology

2.1. Data description

The ETF used as the index proxy is the SPYs.[5] The price of SPYs is 1/10 that of the S&P 500 index level. The data on ETFs, which include tick-by-tick trade prices, the trading volume, quote prices, and quote sizes, are obtained from the NYSE Trade and Quote (TAQ) database. This study retains only trades that occurred during regular trading hours; that is, between 9:30 AM and 4:00 PM (EST). Brunnermeier (2009) indicates that the first wave of funding illiquidity started on August 9, 2007. Accordingly, our sample period starts on February 12, 2007, and ends on December 31, 2008, a period spanning approximately 6 months ("First Period") prior to, and roughly 17 months ("Second Period") after, the start of the credit crunch (i.e., August 9, 2007). Although the occurrence of Lehman Brothers event has an extreme impact on the funding liquidity on September 2008, this study emphasizes the changes in illiquidity contagion in comparison with normal funding liquidity period (First Period) and stressing funding liquidity period (Second Period).

The E-mini version of S&P 500 futures is regarded as the index futures. Hasbrouck (2003) as well as Kurov and Lasser (2004) present evidence showing that small-denomination futures contracts (i.e., E-minis) have a higher price-discovery capability compared to 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. Tick-by-tick data on the S&P 500 index and E-mini futures are obtained from the intraday database of Tick Data Inc.[6]

Numerous previous studies have already provided a comprehensive introduction to the market structures of index futures and ETFs.[7] In brief, regular S&P 500 index futures are traded on the open outcry floor of the Chicago Mercantile Exchange (CME), whereas S&P 500 E-mini index futures are traded on the electronic CME platform. Regular futures and E-mini futures share many similarities. For example, both contracts have the same underlying cash index, expiration date and time, and settlement price, among other factors. However, the main differences between E-mini and regular futures contracts are the contract size and trading hours. The E-mini futures contract multiplier is one-fifth that of the regular futures contract multiplier. In addition, E-mini futures contracts are traded electronically and are available nearly 24 h/day. Thus, E-mini futures are designed for individual or small investors. Chu et al. (1999), Hasbrouck (2003), Tse et al. (2006), and Chen and Chung (2012) report 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 contain more information than those initiated by off-exchange traders, and they provide explanatory evidence for the result regarding the price leadership of E-mini futures contracts reported by Hasbrouck (2003).

ETFs are listed on the AMEX; however, ETF trading occurs across multiple venues. On July 31, 2001, the NYSE began trading the three most active ETFs, namely the NASDAQ-100 Trust Series I, 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.[8] Under the UTP framework, a stock listed on the AMEX can also be traded on other exchanges without a dual listing. Various subsequent studies present evidence on the impact of the UTP system on market quality (e.g., Boehmer & Boehmer, 2003; Tse & Erenburg, 2003).

Although the primary listing exchange for SPYs is the AMEX, the majority of the trading volume and transactions are derived from electronic communication networks (ECNs; e.g., ArcaEx and Island). Until September 2002, the dominant trading platform for major ETFs was the Island ECN, when it stopped displaying its limit order book; this lack of display information led to reduced volumes and higher transaction costs (Hendershott & Jones, 2005a). Consequently, a substantial proportion of the market share of the Island ECN migrated to the ArcaEx ECN, resulting in their market share more than doubling (Tse & Hackard, 2004). When the Island ECN later

[5] Sultan and Zivot (2015) show that although there are multiple ETFs (i.e., SPY, IVV, and VOO) tracking the S&P 500 index, the SPY always contributes more to price discovery than the IVV and VOO.

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

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

[8] An "unlisted trading privilege" is a right granted by the Securities Exchange Act of 1934, which permits securities listed on any national securities exchange to be traded by other such exchanges.

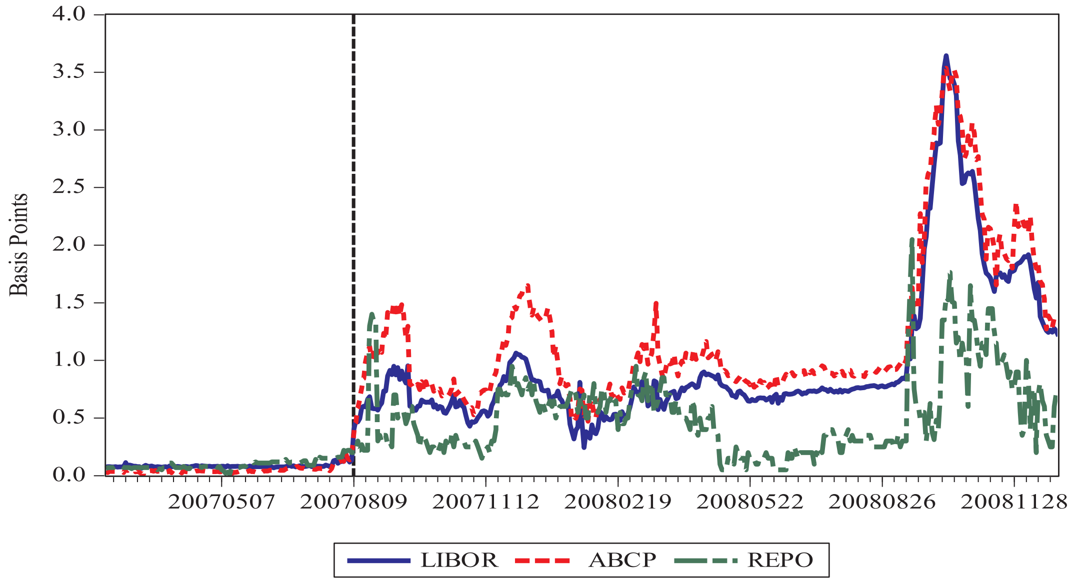

Fig. 1. Measures of funding liquidity. *Note:* This figure plots the time-series daily value of LIBOR, ABCP, and REPO from February 12, 2007 to December 31, 2008. The ABCP is measured by the spread between the 3-month ABCP rate and the overnight index swap; the LIBOR rate is measured by the spread between the U.S. 3-month interbank labor rate and the overnight index swap; and the REPO rate is calculated as the mortgage repossession rate minus the government repossession rate.

chose to redisplay its orders, it was no longer a dominant player in this market. Tse et al. (2006) summarize these two previous studies to show that ETFs traded on the ArcaEx ECN dominated the price-discovery process to a moderate extent for ETF shares in 2004.[9] Chen and Chung (2012) also show that the ArcaEx ECN dominated the price discovery of the SPY market after SPY options were introduced in 2005. Furthermore, Chung and Chuwonganant (2012) report that NASDAQ provided faster and more reliable executions compared to the NYSE/AMEX after the implementation of Regulation National Market System (Reg. NMS) on July 2007. Chen, Chung, and Lien (2016) also indicate that NASDAQ was the dominant contributor to price discovery in the SPY markets in 2007.

In order to ensure accuracy of the sample data, all trades that are out of time sequence are deleted. Data errors are minimized further by eliminating trades that have already fulfilled the criteria outlined in prior studies (Hasbrouck, 2003; Tse et al., 2006). In addition, the trades are screened for outliers with a filter that removes prices that differed by more than 10% from the last prices (i.e., $|(P_t - P_{t-1})/P_{t-1}| > 0.1$).

2.2. Measurement of funding liquidity

Following Chiu et al. (2012), we use LIBOR, which is modeled as the spread between the 3-month U.S. interbank LIBOR rate and the overnight index swap, to measure the capital constraints of the financial intermediaries. In addition, we use asset-backed commercial papers (ABCPs) and Repo in collateral markets to capture hedge funds and the capital constraints of market makers. ABCPs are measured as the spread between 3-month ABCP rates and the overnight index swap, whereas REPO is calculated as the mortgage repossession rate minus the government repossession rate.[10]

Fig. 1 illustrates the patterns of the daily LIBOR, ABCP, and REPO data from February 12, 2007, until December 31, 2007, and shows that these funding liquidity variables change in comovement. The figure also displays a rising pattern in these funding liquidity variables starting in August 2007, and shows a strong likelihood that they would have suffered from funding problems from August 2007 onward. As mentioned in Brunnermeier (2009), the first funding illiquidity wave on the interbank market started on August 9, 2007. Based on this date, this study emphasizes the changes in illiquidity contagion in comparison with normal funding liquidity period and stressing funding liquidity period.

2.3. Measurement of market liquidity

Three well-established liquidity benchmarks are available in the literature. The benchmark is the spread (SP), which is calculated as $SP = (P_{ask} - P_{bid})/P_{mid}$, where P_{ask}, P_{bid}, and P_{mid} are the ask price, bid price, and midpoint, respectively, of these two prices. Because

[9] The Pacific Exchange formed a coalition with the ArcaEx ECN in 2003 to provide an exchange with the ability to electronically trade listed securities; therefore, prior studies had adopted Pacific Exchange data for the ArcaEx ECN.

[10] This study also use the TED spread, which is defined as the difference between the 3-month US Treasury bills and the 3-month LIBOR rate. The results are similar with main findings using three funding liquidity measures.

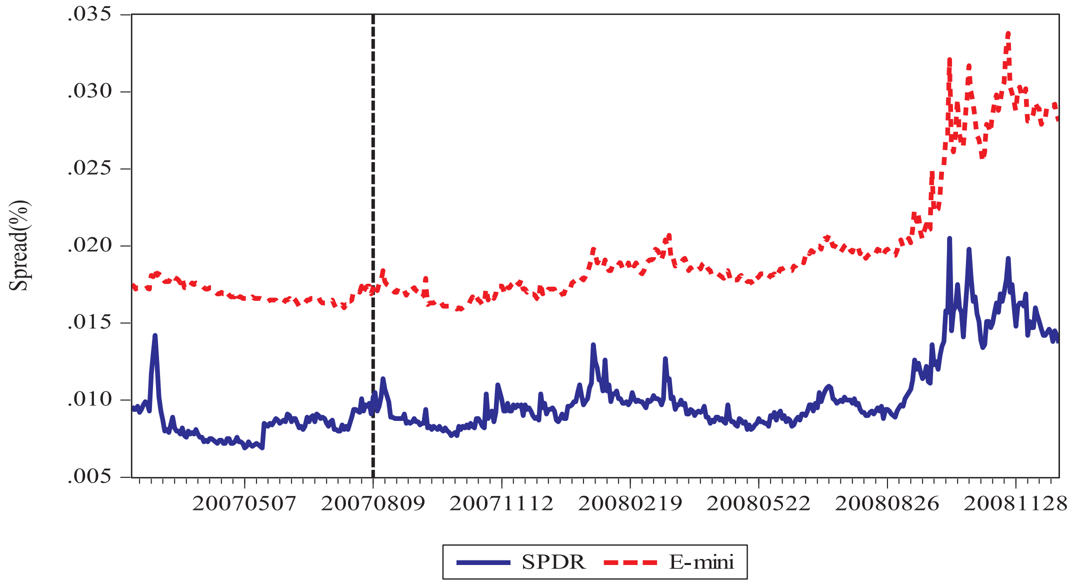

Fig. 2. Percentage spreads of SPYs and S&P 500 E-mini index futures.

direct data on bid-ask spread quotes are unavailable for our data from the Tick Data database, we computed bid-ask spreads by implementing the methodology suggested by Wang, Michalski, Jordan, and Moriarty (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 using the following steps: (1) Create an empirical joint price distribution of ΔP_t and ΔP_{t-1} during a daily interval; (2) Discard the subset of price changes that exhibits price continuity (i.e., a positive change followed by a positive change); (3) Take absolute values of price changes that are price reversals; and (4) Compute the mean of the absolute values obtained in Step (3). Finally, we can estimate the average bid-ask spread for each day in our research period. Consistent with the spread of SPYs, we divide the average bid-ask spread of E-minis by the trade price. Fig. 2 displays the change patterns in the market liquidity of SPYs and E-minis, and clearly shows significant comovement in this regard.

2.4. Measurement of price discovery

In this study, we measure the mechanics of price discovery by using two approaches: (a) the "permanent-transitory" (PT) model discussed by Gonzalo and Granger (1995); and (b) the "information share" (IS) model developed by Hasbrouck (1995). The former focuses on common factor components and the process of error correction, whereas the latter considers the contribution of each market to the variance of innovations in the common factor. These two models are directly related, and provide similar results if the residuals are uncorrelated between markets; however, they typically provide different results in instances of substantive correlation.

As shown in the study of Stock and Watson (1988), the price vector can be decomposed into permanent and transitory components, and the common trend of the price series is expressed as $Y_t = f_t + G_t$, where f_t is the common factor, and G_t is the transitory component with no permanent impact on Y_t. Gonzalo and Granger (1995) decompose the common factor f_t into a linear combination of prices $f_t = \Gamma' Y_t = (\alpha'_{\perp}\beta_{\perp})^{-1}\alpha'_{\perp}Y_t$; where Γ is the common factor coefficient vector and Γ is normalized so that its sum is equal to 1. de Jong (2002) suggests that the coefficients of Γ_i can be interpreted as portfolio weights.

The IS approach requires the estimation of the vector error correction model (VECM). According to the study of Hasbrouck (1995), the VECM can be transformed into a vector moving average (VMA) model, and its integrated form is expressed as follows: $Y_t = \iota\psi(\sum_{i=1}^{t} \varepsilon_i) + \Psi^*(L)\varepsilon_t$, 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} represents the correlation between ε_{it} and ε_{it}. In addition, ι is a column vector of ones; ψ is a common row vector in the impact matrix, which is the sum of the moving average coefficients; and $\Psi(L)$ and $\Psi^*(L)$ represent matrix polynomials in lag operator L.

Hasbrouck (1995) defines the IS of an asset as the proportion of $Var(\psi\varepsilon_t) = \psi\Omega\psi'$ attributable to innovations in that market and the IS is obtained as $IS_j = \frac{([\psi F]_j)^2}{\psi\Omega\psi'}$, where F is a lower triangular matrix by applying the Cholesky factorization of $\Omega = FF'$, and $[\psi F]_j$ is the jth element of the row of matrix ψF. A market's contribution to price discovery is measured as the market's relative contribution to the variance of innovation in the common trend.[11]

[11] Furthermore, Baillie, Booth, Tse, and Zabotina (2002) show an easier method of calculating ISs directly from VECM results, without requiring VMA representation. The calculation of ISs is based on the VECM in the study. See, for example, Hasbrouck (2003) and Tse et al. (2006).

The IS's results 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) IS, and this discrepancy may be large if the series' innovations are highly and contemporaneously correlated. Lien and Shrestha (2009) propose a modified information share (MIS) model which provides a unique measure of price discovery by using the factorization matrix based on the correlation matrix.

Following the study of Lien and Shrestha (2009), Φ denotes the innovation correlation matrix, and Λ is the diagonal matrix, with diagonal elements representing the eigenvalues of correlation matrix Φ, where the corresponding eigenvectors are obtained with the columns of matrix G. In addition, V denotes a diagonal matrix containing the innovation standard deviations on the diagonal; that is, $V = \text{diag}(\sqrt{\Omega_{11}},\ldots,\sqrt{\Omega_{nn}})$. By transforming $F^* = [G\Lambda^{-1/2}G'V^{-1}]^{-1}$ from $\Omega = F^*(F^*)'$, the MIS is obtained by $IS_j^* = \frac{\psi_j^{*2}}{\psi\Omega\psi'}$, where $\psi^* = \psi F^*$. Under this new factor framework, Lien and Shrestha (2009) show that the resultant ISs are independent of ordering, which leads to a measure of price discovery that is order invariant, suggesting that the MIS measure outperforms both the IS and PT measures. In addition, Lien and Wang (2016) also show that MIS measure provides at most marginal improvement over the method based upon the upper/lower bound midpoint of the Hasbrouck measure.

2.5. Regression analysis in market liquidity

This study investigates the impact of funding liquidity on the market quality of SPYs and S&P 500 index futures. For this study, we follow prior research (Bollen & Whaley, 1998; Chordia, Roll, & Subrahmanyam, 2011; Hameed et al., 2010; Hendershott, Jones, & Menkveld, 2011) to devise our regression model, by adopting the number of trades, market volatility, market return, and funding liquidity as control variables. To probe the argument presented by Cespa and Foucault (2014), we consider respectively the impact of SPY liquidity on E-mini liquidity and the impact of E-mini liquidity on SPY liquidity. We thus analyze changes in the market liquidity of E-mini and SPY by using the regression models defined in the following two Eqs. (1) and (2):

$$FSP_t = \beta_0 + \beta_1\log(FNT_t) + \beta_2 FSig_t + \beta_3 FRet_t + \beta_4 SSP_t + \beta_5 FundLiq_t + \varepsilon_t \tag{1}$$

$$SSP_t = \beta_0 + \beta_1\log(SNT_t) + \beta_2 SSig_t + \beta_3 SRet_t + \beta_4 FSP_t + \beta_5 FundLiq_t + \varepsilon_t \tag{2}$$

where t denotes the daily time interval; FSP_t and SSP_t refer respectively to the daily market liquidity for E-mini and SPY as measured by the spread during trading day t; FNT_t and SNT_t are respectively the number of trades for E-mini and SPY during trading day t; $FSig_t$ and $SSig_t$ represent respectively the Parkinson (1980) extreme value estimator, which proxies for the volatility of E-mini and SPY on trading day t; $FRet_t$ and $SRet_t$ denote respectively the returns in E-mini and SPY during trading day t; and $FundLiq_t$ denotes the funding liquidity measure, including LIBOR, ABCPs, and REPO, on trading day t.

To consider the endogeneity of the spreads between SPYs and E-minis in the liquidity regression models, we estimate the models by using the generalized method of moments, which employs the lagged spread and lagged volatility as 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 raises the likelihood of an adverse price move, resulting in poor liquidity. A negative coefficient on the return variable is expected if the negative market return is harmful to market liquidity (Hameed et al., 2010). If market liquidity deteriorates because of funding illiquidity, then this indicates an increase in market impact costs. Therefore, a positive coefficient on funding liquidity is also expected.

2.6. Regression analysis in price discovery

This study investigates the impact of funding liquidity on the market quality of SPYs and S&P 500 index futures. Thus, we follow prior studies (Ates & Wang, 2005; Chakravarty, Gulen, & Mayhew, 2004; Chen & Chung, 2012) to control for other factors by examining changes in the market liquidity and price discovery of SPYs and S&P 500 index futures.

To examine the arguments positing that a change in the contribution of SPYs and S&P 500 index futures to price discovery is associated with market factors, for this study we devise a regression model to adopt similar control variables, including the number of trades and market volatility. Chakravarty et al. (2004) argue that price discovery is related to the number of trades, the spread, return, volatility, and funding liquidity. We examine the change in the level of price discovery after August 10, 2007, using the regression model defined in the following equation:

$$\log\left(\frac{PD}{1-PD}\right)_t = \beta_0 + \beta_1\log\left(\frac{SVol}{FVol}\right)_t + \beta_2\log\left(\frac{SNT}{FNT}\right)_t + \beta_3\log\left(\frac{SSP}{FSP}\right)_t + \beta_4 Sigma_t + \beta_5 FundLiq_t + \varepsilon_t \tag{3}$$

where t denotes the daily time interval; PD_t represents the daily share of information for SPYs as measured by the PT, IS, and MIS models for SPY trades compared with E-mini futures; $SVol_t$ ($FVol_t$) refers to the trade volume for SPYs (E-minis) during trading day t; SNT_t (FNT_t) is the number of trades for SPYs (E-minis) during trading day t; SSP_t (FSP_t) represents the daily market liquidity for SPYs (E-minis) measured by the spread during trading day t; $Sigma_t$ denotes the Parkinson (1980) extreme value estimator, which proxies for the volatility of the S&P 500 index markets on trading day t; and $FundLiq_t$ represents the funding liquidity measure, including LIBOR, ABCPs, and REPO, on trading day t.

According to the transaction cost hypothesis, a 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) and Chen et al. (2016) indicate that a greater share of information is found in the E-mini

Table 1
Summary statistics of SPYs and E-mini S&P500 index futures.

Symbol	Number of trades	Trade volume (100 shares/ contact)	Quoted Spread (%)	Avg. size per trade (100 shares /contact)	Transactions by size (contracts)		
					Small size	Medium size	Large size
Panel A: First Period (12 February 2007–9 August 2007, 125 trading days)							
SPY	21,837,263	162,224,383	0.0198	7.43	55.92%	43.62%	0.47%
E-mini	9,993,501	153,740,437	0.0169	15.38	76.52%	20.26%	3.22%
Panel B: Second Period (10 August 2007–31 December 2008, 352 trading days)							
SPY	168,853,115	853,404,234	0.0253	5.05	69.25%	30.50%	0.25%
E-mini	67,048,387	648,865,789	0.0202	9.68	81.64%	16.85%	1.51%

Note: This table presents the transactions and trading volumes of SPYs on all exchanges and E-mini S&P 500 index futures on the 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). For the E-mini, this study defines small trades as those consisting of 1–9 contracts, medium-sized trades as 10–99 contracts, and large (block) trades as 100 contracts or more. We computed quoted bid-ask spreads by implementing the methodology suggested by Wang et al. (1994). For the SPY, This study defines small trades as those consisting of 1–499 shares, medium-sized trades as 500–9999 shares, and large (block) trades as 10,000 shares or greater. The quoted spread of SPYs is calculated as $[(P_{ask} - P_{bid})/P_{mid}]$, where P_{ask} is the ask price, P_{bid} represents the bid price, and P_{mid} is the midpoint of the bid and ask prices of the quotes.

futures market during periods of high volatility. This study argues that E-mini futures make a significantly higher contribution to price discovery during periods of high volatility because institutional investors and/or informed traders typically use derivatives to fulfill the hedge requirement. A negative relationship between the IS of SPYs and market volatility is expected. Finally, if market liquidity deteriorates because of funding illiquidity, then this indicates an increase in market impact costs. Therefore, a negative coefficient on funding liquidity is also expected.

3. Empirical results

3.1. Summary statistics of the SPY and E-minis

Table 1 shows the summary statistics of SPYs and E-mini futures, listing data about the number of transactions, trading volumes, quoted spreads, and average trade size.[12] Consistent with prior studies (Barclay & Warner, 1993; Chakravarty, 2001), the present study defines small trades as those consisting of 1–499 shares, medium-sized trades as 500–9999 shares, and large (block) trades as 10,000 shares or more. Based on our observations of the size distribution of transactions in the first period, 55.92% of the SPY trades were small trades, 43.62% were medium-sized trades, and 0.47% were block trades. In the second period, 69.25% were small trades, 30.50% were medium-sized trades, and 0.25% were block trades.

Table 1 shows comprehensive details regarding the number of trades, trade size, and transactions by trade size, in E-mini futures on the CME. This study defines small trades as those consisting of 1–9 contracts, medium-sized trades as 10–99 contracts, and large (block) trades as 100 contracts or more. Table 1 shows that most transactions are attributable to small trades. Therefore, small 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 transactions shows that the demand for hedge generally increased during the 2007–2008 credit crunch.

The increased patterns in quoted spreads show a decrease in market liquidity in the SPY and E-mini S&P 500 index futures markets, indicating that market liquidity of SPYs and E-minis may be associated with funding liquidity. This finding, which shows that the market liquidity of SPYs exhibits a decreasing pattern in the second period, is consistent with that obtained by Chiu et al. (2012), who report that lower market liquidity was accompanied by an increase in funding illiquidity in 2007–2008.

3.2. Price discovery analyses in E-minis and SPYs

Prior studies suggest that E-mini futures contribute the most to price discovery (Chu et al., 1999; Hasbrouck, 2003), and that ETFs play a significant role in the price-discovery process (Chen & Chung, 2012; Chen et al., 2016; Tse et al., 2006). The price-discovery results obtained using the PT and MIS models for the S&P 500 index, E-mini futures, and SPYs are shown in Table 2..[13] The results of the PT and MIS models indicate that, compared to the other markets, SPYs are relatively dominant, making a significant contribution to the price-discovery process in the first and second periods.

The finding, showing that SPYs appear to lead E-mini futures significantly, reflects the importance of SPYs in the price-discovery process of the S&P 500 index markets. This result is consistent with that of Chen et al. (2016), and reemphasizes the significance of

[12] For the details in trades and quotes of the SPY, the results of all exchanges are presented in Table A1. In summary, most of the transactions and trading volume are attributable to the NYSE Arca and NASDAQ. This study infers that most of the information available on SPY prices may be due to these two exchanges. The liquidity analysis results of SPYs show that NASDAQ has the lowest spread and highest market quality index in the first and second periods, thus indicating that higher liquidity leads to a lower market impact cost in overall transaction costs.

[13] According to prior studies (Hasbrouck, 1995, 2003; Kurov & Lasser, 2004; Tse et al., 2006), price-discovery analysis adopts matched time series with 1-s intervals between observations and lagged terms of up to 5 min, as in Hasbrouck (2003). If a price is not reported at a particular second, the previous available price is used. In addition, only the last trade price is used if several trades are reported with the same timestamp.

Table 2
Price discovery analysis in S&P 500 index, E-mini futures and SPYs markets.

	S&P 500 Index	E-mini Futures	SPYs
Panel A: First Period (12 February 2007–9 August 2007, 125 trading days)			
PT Model	0.1684	0.2537	0.5779
IS Model	0.0493	0.4137	0.5371
MIS Model	0.0493	0.4125	0.5382
Panel B: Second Period (10 August 2007–31 December 2008, 352 trading days)			
PT Model	0.1453	0.2626	0.5921
IS Model	0.0455	0.3479	0.6067
MIS Model	0.0455	0.3208	0.6337

Note: The results of price discovery obtained using the common factor (PT), information share, and modified information share models are reported for the S&P 500 spot index, E-mini futures, and SPYs. The statistics are based on a vector error correction model of prices for these variables, estimated as 1-s resolution data. The models are estimated for each day during our sample period (from February 12, 2007, to December 31, 2008). The daily estimates are calculated from the average of the price-discovery measures of all permutations of the order of variables in the estimation process. The figures throughout the table represent the means of the daily measures of price discovery.

ETFs in contributing to price discovery. Furthermore, SPYs make more contributions to price discovery in the second period than in the first period, showing a greater impact of funding illiquidity on E-minis than on SPYs.

3.3. Regression analyses in market liquidity of E-minis and SPYs

This study investigates the impact of funding liquidity on market quality. We first observe changes in market liquidity for E-minis and SPYs, before and after the start of the credit crunch.

Panel A of Table 3 shows the results of regression analysis for the market liquidity of E-minis, obtained by measuring spreads (*FSP*) in the first period.[14] In Specifications (1)–(7), the results show that the estimated coefficient on market volatility is significantly positive in the liquidity regression model, indicating that higher market risk leads to a reduction in market liquidity. The results are similar to those presented in prior studies (Amihud & Mendelson, 1987; Chiu et al., 2012; McInish & Wood, 1992) that report volatility to have a positive impact on the spread. In Specifications (2) through (7), we find that the influences of funding liquidity variables on liquidity are inconsistent, indicating that funding liquidity may not have been an important determinant of the liquidity of E-minis before the start of the credit crunch. In Specifications (1), (3), (5), and (7), the estimated coefficients on SPY liquidity (*SSP*) are significantly positive in the E-mini liquidity regression, showing that SPY liquidity affects E-mini liquidity, even when the effect of funding liquidity is accounted for in the regression models.

Panel B of Table 3 shows the results of regression analysis for the market liquidity of E-minis, obtained by measuring spreads (*FSP*) in the second period. In Specifications (9), (11), and (13), the estimated coefficients on funding liquidity are significantly positive, except for REPO, indicating that funding liquidity affected the market liquidity of E-minis during the credit crunch. In Specifications (10), (12), and (14), we simultaneously consider the effects of funding liquidity and SPY liquidity on E-mini liquidity. However, the effect of funding liquidity is offset by that of SPY liquidity, indicating that SPY liquidity acts as an important mediator in the relationship between funding liquidity and E-mini liquidity during periods of market decline.

Panel A of Table 4 lists the results of regression analysis for the market liquidity of SPYs, obtained by measuring spreads (*SSP*) in the first period. In Specifications (1) through (7), the results show that the estimated coefficient on the number of trades is significantly negative, whereas on market volatility it is significantly positive in the liquidity regression model. These results show that lower trading frequency and higher market risk lead to a reduction in market liquidity. In Specifications (2) through (7), we find that the influences of funding liquidity variables on liquidity are significantly positive, indicating that funding liquidity was an important determinant for the liquidity of SPYs before the start of the credit crunch. In Specifications (1), (3), (5), and (7), the estimated coefficients on E-mini liquidity (*FSP*) are insignificant in the SPY liquidity regression, showing that E-mini liquidity does not seem to affect SPY liquidity during normal periods.

Panel B of Table 4 lists the results of regression analysis for the market liquidity of SPYs, obtained by measuring spreads (*SSP*) in the second period. In Specifications (9), (11), and (13), the estimated coefficients on funding liquidity are all significantly positive, showing that funding liquidity affected the market liquidity of SPYs during the subprime mortgage crisis. In Specifications (10), (12), and (14), we simultaneously consider the effects of funding liquidity and E-mini liquidity on SPY liquidity. However, the effect of funding liquidity is partially offset by that of E-mini liquidity, indicating that E-mini liquidity acts as an important mediator in the relationship between funding liquidity and SPY liquidity during periods of market decline.

For the regression results of three funding liquidity measures, LIBOR has a more significant and expected impact than the other two funding liquidity variables on the liquidity in this study. According to Chiu et al. (2012), LIBOR has a much more significant impact than the other two funding liquidity variables on the market liquidity. Banks will charge higher interest for unsecured loans in an environment of higher uncertainty, resulting in increases in the LIBOR rate. Our empirical results are consistent with those of Chiu et al. (2012), who suggest that both intermediaries and arbitrageurs did not have easy access to sufficient funding to provide liquidity

[14] Because this study does not provide quote data of the E-mini S&P 500 index futures, we estimate spreads only from trade prices to proxy market liquidity.

Table 3
Regression analyses of market liquidity for E-mini S&P 500 index futures.

Variable	Panel A: First period (12 February 2007–9 August 2007, 125 trading days)							Panel B: Second Period (10 August 2007–31 December 2008, 352 trading days)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Constant	2.026***	2.296***	2.016***	2.366***	2.066***	1.729***	1.484***	1.832***	0.594	1.570***	0.678	1.539***	0.967	1.685***
	(11.445)	(9.184)	(8.785)	(11.746)	(10.963)	(6.095)	(6.861)	(3.886)	(0.355)	(3.685)	(0.436)	(3.358)	(0.523)	(3.966)
log(*FNT*)	−0.054***	−0.061**	−0.052**	−0.068***	−0.058***	−0.001	0.005	−0.142***	0.077	−0.119***	0.073	−0.113***	0.055	−0.137***
	−(3.146)	−(2.515)	−(2.409)	−(3.462)	−(3.178)	−(0.048)	(0.246)	−(3.369)	(0.530)	−(3.193)	(0.540)	−(2.796)	(0.343)	−(3.682)
FSig	0.062***	0.127***	0.064***	0.126***	0.063***	0.095***	0.037*	0.001	0.141**	−0.005	0.115**	−0.007	0.232***	−0.012
	(3.189)	(5.645)	(3.184)	(5.549)	(3.186)	(4.338)	(1.949)	(0.028)	(2.447)	−(0.289)	(2.256)	−(0.350)	(3.642)	−(0.661)
FRet	0.006	0.009	0.006	0.010	0.007	0.010*	0.008	−0.006*	0.010	−0.004	0.010	−0.003	0.005	−0.005
	(1.121)	(1.439)	(1.151)	(1.531)	(1.228)	(1.748)	(1.531)	−(1.774)	(1.206)	−(1.363)	(1.198)	−(1.129)	(0.569)	−(1.522)
SSP	0.274***		0.262***		0.272***		0.241***	1.783***		1.802***		1.729***		1.966***
	(4.348)		(3.933)		(4.114)		(5.064)	(20.435)		(15.978)		(13.837)		(24.860)
ABCP		−0.093	−0.013						0.245***	−0.011				
		−(0.419)	−(0.078)						(4.279)	−(0.309)				
LIBOR				0.086	0.098						0.304***	0.030		
				(0.657)	(0.840)						(3.921)	(0.682)		
REPO						−0.815***	−0.821***						0.117	−0.175***
						−(2.641)	−(2.951)						(1.569)	−(4.357)
Adj. R^2	0.173	0.157	0.176	0.157	0.169	0.331	0.378	0.916	0.652	0.915	0.670	0.916	0.584	0.919

Note: Changes in the market liquidity of index futures are tested using the following regression model (Eq. (1)).

$$FSP_t = \beta_0 + \beta_1 \log(FNT_t) + \beta_2 FSig_t + \beta_3 FRet_t + \beta_4 SSP_t + \beta_5 FundLiq_t + \varepsilon_t \tag{1}$$

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 moments approach, which uses the lagged spread and lagged volatility as instrumental variables for the SPY spreads. 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 4
Regression analyses of market liquidity for SPYs.

Variable	Panel A: First period (12 February 2007–9 August 2007, 125 trading days)							Panel B: Second period (10 August 2007–31 December 2008, 352 trading days)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Constant	1.523^{**}	2.097^{***}	1.859^{***}	1.873^{***}	1.650^{**}	2.410^{***}	1.579^{***}	0.261	-0.837^{**}	0.061	-0.705^{*}	0.109	-0.999^{**}	0.041
	(2.308)	(3.617)	(3.094)	(3.158)	(2.525)	(4.521)	(3.177)	(1.496)	−(2.208)	(0.348)	−(1.720)	(0.619)	−(2.335)	(0.278)
log(*SNT*)	−0.035	-0.126^{**}	−0.070	-0.107^{*}	−0.047	-0.160^{***}	-0.103^{**}	−0.015	0.133^{***}	0.002	0.124^{***}	−0.003	0.150^{***}	0.003
	−(0.683)	−(2.335)	−(1.436)	−(1.940)	−(0.920)	−(3.238)	−(2.248)	−(0.999)	(4.119)	(0.102)	(3.502)	−(0.186)	(4.140)	(0.195)
SSig	0.171^{***}	0.252^{***}	0.150^{***}	0.260^{***}	0.161^{***}	0.276^{***}	0.147^{***}	0.078^{***}	0.077^{***}	0.056^{***}	0.074^{***}	0.058^{***}	0.097^{***}	0.055^{***}
	(3.045)	(2.961)	(2.693)	(3.155)	(2.829)	(3.278)	(2.874)	(7.291)	(4.276)	(4.253)	(3.914)	(4.270)	(5.032)	(5.690)
SRet	0.000	0.003	0.000	0.005	0.002	0.000	−0.008	0.005^{*}	0.008^{*}	0.003	0.008^{*}	0.003	0.006	0.004^{*}
	(0.021)	(0.281)	−(0.039)	(0.452)	(0.247)	−(0.026)	−(0.805)	(1.887)	(1.853)	(1.560)	(1.764)	(1.445)	(1.339)	(1.804)
FSP	−0.236		−0.216		−0.253		0.120	0.430^{***}		0.420^{***}		0.430^{***}		0.422^{***}
	−(1.074)		−(1.030)		−(1.163)		(0.591)	(19.924)		(20.596)		(23.230)		(17.644)
ABCP		0.675^{***}	0.819^{***}						0.127^{***}	0.038^{**}				
		(2.271)	(2.797)						(4.471)	(2.312)				
LIBOR				0.368^{***}	0.498^{***}						0.140^{***}	0.027		
				(2.649)	(3.302)						(3.690)	(1.460)		
REPO						0.984^{***}	1.367^{***}						0.150^{***}	0.098^{***}
						(2.954)	(5.398)						(3.923)	(5.465)
Adj. R^2	0.203	0.360	0.235	0.333	0.202	0.391	0.322	0.931	0.783	0.933	0.781	0.932	0.759	0.941

Note: Changes in SPY market liquidity are tested using the following regression model (Eq. (2)).

$$SSP_t = \beta_0 + \beta_1 \log(SNT_t) + \beta_2 SSig_t + \beta_3 SRet_t + \beta_4 FSP_t + \beta_5 FundLiq_t + \varepsilon_t \quad (2)$$

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 SPYs during trading day t; $SSig_t$ is the Parkinson (1980) extreme value estimator, which proxies for the volatility of SPYs; $SRet_t$ is the market return for SPYs 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 moments approach, which uses the lagged spread and lagged volatility as the instrumental variables for E-mini spreads. 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.

to the market and raise the quoted spread.

In addition, the effect of own volatility on market liquidity declines significantly, while the effect of other market liquidity increases significantly for both SPY and E-mini markets. Ben-David, Franzoni, and Moussawi (2014) show that arbitrage activity between ETFs and the underlying securities leads to an increase in stock volatility, conjecturing that arbitrage trades propagate liquidity shocks in the ETF market to the prices of underlying securities. Since volatility of SPY and E-mini markets is based on volatility of the component stocks, higher spread results in increased trading costs for arbitrageurs. Pan and Zeng (2016) indicate that arbitrageurs may not be willing to engage in arbitrage when the component stocks are illiquid. Sometimes, authorized participants (APs) have a dual role of APs and market makers in financial markets, and they may occasionally consume more liquidity than they provide. Specifically, Krause, Ehsani, and Lien (2014) find that volatility spillovers from ETFs to their component stocks are increasing in liquidity, supporting a positive volume-volatility relation and trading-based explanations of volatility. This study infers that trading activities and volatility spillovers are impeded by illiquidity, and further lower the impacts of volatility on liquidity.

Overall, the results show evidence of the spillover effect in the relationship of liquidity between SPYs and E-minis, supporting the argument made by Cespa and Foucault (2014) regarding contagion in asset illiquidities.[15] We conjecture that the influence of funding liquidity on E-mini liquidity is partially derived from the SPYs.

3.4. Regression analyses on the price discovery of E-minis and SPYs

To provide evidence that a decrease in market liquidity and funding liquidity affects the contribution to price discovery, Table 5 shows detailed results on the relationships between trade price discovery and control variables, based on regression analysis.

Panel A of Table 5 shows the regression analysis results for the price discovery of SPYs as measured by PT and MIS models for SPY trades, compared with E-mini futures prices in the first period. The coefficients on the spread ratio variable reveal a significantly negative explanatory power on the price-discovery measures, implying that the transaction-cost hypothesis helps explain the effect of market liquidity on price discovery. In addition, the coefficients on the volatility variable (*Sigma*) reveal a significantly negative explanatory power of market volatility on the price-discovery measures, implying that the leverage effect in price-discovery analysis is strengthened during periods of high volatility. Finally, we find that the coefficients on funding illiquidity (*FundLiq*) have insignificant positive explanatory power, thus showing a mixed influence of funding liquidity on the contributions of E-mini index futures and SPYs to price discovery during normal periods.

Panel B of Table 5 shows the results of regression analysis for the price discovery of SPYs, as measured by the PT and MIS models for SPY trades, compared with E-mini futures prices in the second period. The coefficients on the spread ratio still reveal a significantly negative explanatory power on the price-discovery measures. Conversely, the coefficients on the volatility variable (*Sigma*) and funding illiquidity (*FundLiq*) reveal respectively an insignificantly negative and an insignificantly positive explanatory power on the price-discovery measures, except for models (2) and (3). These results show that liquidity affected price discovery during the subprime mortgage crisis, implying that the liquidity spillover between SPYs and E-minis strengthens the liquidity effect on price discovery.

In the price-discovery analysis for both SPY and E-mini markets, the effects of market volatility change across the two sub-periods significantly. The leverage effect in price-discovery analysis is invalid during the high funding illiquidity period. As noted in Brunnermeier (2009), traders tend not to carry much excess capital and increasing margins during a higher funding illiquidity period, and haircuts force traders to de-leverage their position. Therefore, the effect of market volatility on the contribution of E-minis to price discovery is insignificant in the second period.

Overall, Table 5 shows that all of the coefficients on the funding illiquidity variable are insignificantly positive, indicating that the overall influence of funding illiquidity on price discovery of E-minis is higher than that of SPYs, because of the liquidity spillover between SPYs and E-minis. However, we find market volatility to be a crucial determinant in the price-discovery process.

4. Conclusion

This study analyzes changes in market quality before and after the 2007 credit crunch by examining the impact of funding liquidity on market liquidity and the 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 are examined. The empirical results show that funding illiquidity affects the market liquidity of SPYs and E-minis. With an increase in funding illiquidity during the subprime mortgage crisis, a significant illiquidity contagion occurs between SPYs and E-minis. This result is consistent with the argument presented by Cespa and Foucault (2014), who suggest liquidity providers in one asset class often learn information from other asset price

In addition, we find that funding illiquidity has a greater influence on the contribution of E-mini index futures to price discovery compared with SPYs. Considering the effects of other market factors on the contribution to price discovery, we suggest that E-mini index futures made less contributions to price discovery during the credit crunch compared to normal periods The contagion effects between the two markets mediated the impact of funding illiquidity on market liquidity during the credit crunch, showing the important influence of spillovers on market liquidity and price discovery for SPYs and E-mini index futures. Overall, the empirical finding emphasizes that the liquidity spillover mediate the importance of funding illiquidity in affecting market liquidity, implying that the influence of contagion effect between ETF and E-mini index futures markets is higher than external shocks.

[15] Since we estimate the regression models by using the generalized method of moments, which employs the lagged spread and lagged volatility as instrumental variables for the spread, the significant coefficients of spread variable also imply spillover or contagion effects between SPYs and E-minis.

Table 5
Regression analyses of price discovery for SPYs and E-minis.

Variable	PT Model				MIS Model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: First period (12 February 2007–9 August 2007, 125 trading days)								
Constant	−0.630	−0.017	−0.498	−0.409	−3.391	−1.982	−3.138	−2.825
	−(0.279)	−(0.007)	−(0.224)	−(0.171)	−(1.082)	−(0.682)	−(1.066)	−(0.891)
$\log\left(\frac{SVol}{FVol}\right)$	−0.052	−0.316	−0.200	−0.328	0.535	−0.072	0.251	−0.172
	−(0.095)	−(0.481)	−(0.346)	−(0.476)	(0.694)	−(0.100)	(0.351)	−(0.223)
$\log\left(\frac{SNT}{FNT}\right)$	0.741	0.787	0.776	0.628	0.712	0.819	0.779	0.422
	(0.860)	(0.896)	(0.897)	(0.732)	(0.718)	(0.803)	(0.783)	(0.383)
$\log\left(\frac{SSP}{FSP}\right)$	−3.012**	−3.357**	−3.118**	−3.711**	−3.312*	−4.106**	−3.515**	−5.100**
	−(2.375)	−(2.486)	−(2.466)	−(2.265)	−(1.963)	−(2.353)	−(2.117)	−(2.496)
Sigma	−0.892*	−1.068**	−1.092**	−0.956**	−1.309	−1.713*	−1.694*	−1.472*
	−(1.898)	−(2.186)	−(2.139)	−(2.026)	−(1.575)	−(1.807)	−(1.806)	−(1.732)
ABCP		4.309				9.919*		
		(0.891)				(1.760)		
LIBOR			5.318				10.200*	
			(1.050)				(1.932)	
REPO				3.898				9.970
				(0.889)				(1.593)
Adj. R^2	0.223	0.226	0.227	0.223	0.228	0.254	0.248	0.251
Panel B: Second period (10 August 2007–31 December 2008, 352 trading days)								
Constant	−6.263**	−6.605**	−6.433**	−6.431**	−13.484**	−13.822**	−13.674**	−13.653**
	−(2.113)	−(2.185)	−(2.107)	−(2.186)	−(2.323)	−(2.391)	−(2.336)	−(2.358)
$\log\left(\frac{SVol}{FVol}\right)$	0.702	0.710	0.695	0.665	2.110	2.118	2.102	2.073
	(1.084)	(1.068)	(1.034)	(1.006)	(1.610)	(1.600)	(1.575)	(1.566)
$\log\left(\frac{SNT}{FNT}\right)$	−0.573	−0.688	−0.704	−0.543	0.748	0.635	0.603	0.779
	−(0.763)	−(0.895)	−(0.905)	−(0.717)	(0.640)	(0.543)	(0.507)	(0.662)
$\log\left(\frac{SSP}{FSP}\right)$	−7.321***	−7.590***	−7.489***	−7.664***	−9.358***	−9.625***	−9.546***	−9.704***
	−(4.339)	−(4.310)	−(4.328)	−(4.447)	−(3.443)	−(3.596)	−(3.565)	−(3.548)
Sigma	−0.060	−0.145*	−0.171**	−0.092	−0.086	−0.171	−0.211	−0.118
	−(0.776)	−(1.766)	−(1.993)	−(1.000)	−(0.603)	−(0.898)	−(0.962)	−(0.766)
ABCP		0.235*				0.233		
		(1.664)				(0.876)		
LIBOR			0.291*				0.325	
			(1.915)				(0.993)	
REPO				0.249				0.251
				(0.829)				(0.624)
Adj. R^2	0.118	0.120	0.121	0.117	0.163	0.162	0.163	0.161

Note: Changes in the contribution of SPYs to price discovery relative to E-mini index futures are tested based on the following regression model (Eq. (3)).

$$\log\left(\frac{PD}{1-PD}\right)_t = \beta_0 + \beta_1 \log\left(\frac{SVol}{FVol}\right)_t + \beta_2 \log\left(\frac{SNT}{FNT}\right)_t + \beta_3 \log\left(\frac{SSP}{FSP}\right)_t + \beta_4 Sigma_t + \beta_5 FundLiq_t + \varepsilon_t \tag{3}$$

where t indicates the daily time interval; PD_t refers to the daily share of information for SPYs measured by the common factor (PT) and modified information share (MIS) models for SPY trades compared with E-mini futures prices during trading day t; $SVol_t$ ($FVol_t$) is the trade volume for SPYs (E-minis) during trading day t; SNT_t (FNT_t) is the number of trades for SPYs (E-minis) during trading day t; SSP_t (FSP_t) refers to the daily market liquidity for SPYs (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 markets on trading day t; and $FundLiq_t$ is the funding liquidity measure, including LIBOR, ABCP, and REPO, on 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.

Acknowledgement

Chih-Chiang Wu and Wei-Peng Chen gratefully acknowledge financial support from the Ministry of Science and Technology of Taiwan.

Appendix A

Table A1.

Table A1
Trades and quotes of SPYs in different trading centers.

Trading centers	Number of trades (%)	Trade volume (100 shares) (%)	Avg. size per trade (100 shares)	Transactions by size (shares)			Number of quotes (%)	Quoted depth (100 shares)	Quoted spread (%)	Market quality index (*MQI*)
				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%)	(2.90%)	145.35	0.0344	27.27
B (Boston)	(0.08%)	(0.03%)	2.52	(0.13%)	(0.02%)	(0.00%)	(0.00%)	12.32	0.4376	0.32
C (NSX)	(0.88%)	(0.81%)	6.83	(0.93%)	(0.82%)	(0.77%)	(21.49%)	420.67	0.0127	160.71
D (NASD ADF/TRF)	(5.72%)	(19.13%)	24.84	(5.65%)	(5.71%)	(16.07%)	(3.14%)	194.61	0.0488	35.03
I (ISE)	(0.42%)	(0.31%)	5.47	(0.54%)	(0.28%)	(0.07%)	(10.59%)	70.27	0.0277	19.83
M (Chicago)	(0.01%)	(0.65%)	768.44	(0.00%)	(0.00%)	(0.69%)	(0.00%)	10.25	0.1270	0.54
N (NYSE)	(0.41%)	(0.42%)	7.54	(0.51%)	(0.29%)	(0.68%)	(1.86%)	51.53	0.0719	4.72
P (NYSE Arca)	(33.77%)	(36.11%)	7.94	(26.05%)	(43.56%)	(43.07%)	(19.80%)	590.65	0.0091	318.42
T (NASDAQ)	(57.48%)	(40.57%)	5.24	(64.89%)	(48.24%)	(33.90%)	(38.55%)	575.08	0.0086	328.53
W (CBOE)	(0.12%)	(0.50%)	30.54	(0.10%)	(0.13%)	(2.48%)	(1.67%)	317.80	0.3034	29.96
X (Philadelphia)	(0.00%)	(0.02%)	841.08	(0.00%)	(0.00%)	(0.02%)	(0.00%)	2.00	0.0139	0.72
Total	21,837,263	162,224,383	7.43	12,210,540	9,524,829	101,894	81,671,193	453.03	0.0198	228.79
Panel B: Second Period (10 August 2007–31 December 2008, 352 trading days)										
A (AMEX)	(0.59%)	(0.89%)	7.70	(0.54%)	(0.68%)	(1.89%)	(3.21%)	113.95	0.0694	9.99
B (Boston)	(0.00%)	(0.00%)	4.03	(0.00%)	(0.00%)	(0.00%)	(0.00%)	97.85	0.3304	5.41
C (NSX)	(1.16%)	(1.10%)	4.78	(1.22%)	(1.03%)	(1.35%)	(24.06%)	137.38	0.0164	51.78
D (NASD ADF/TRF)	(13.66%)	(20.67%)	7.65	(13.16%)	(14.76%)	(18.59%)	(1.04%)	115.97	0.0780	9.67
I (ISE)	(0.36%)	(0.27%)	3.86	(0.40%)	(0.26%)	(0.19%)	(7.71%)	71.42	0.0453	26.28
M (Chicago)	(0.30%)	(1.35%)	22.83	(0.20%)	(0.49%)	(3.50%)	(3.97%)	409.00	0.0538	44.43
N (NYSE)	(0.00%)	(0.01%)	9.80	(0.00%)	(0.00%)	(0.02%)	(0.01%)	102.82	0.1183	4.62
P (NYSE Arca)	(24.95%)	(27.08%)	5.48	(22.62%)	(30.16%)	(34.58%)	(17.62%)	153.73	0.0145	65.93
T (NASDAQ)	(56.03%)	(46.21%)	4.17	(58.43%)	(50.74%)	(36.84%)	(31.28%)	196.05	0.0113	100.03
W (CBOE)	(0.11%)	(0.68%)	29.77	(0.07%)	(0.19%)	(2.56%)	(2.15%)	207.05	0.2064	11.06
X (Philadelphia)	(0.00%)	(0.04%)	129.83	(0.00%)	(0.00%)	(0.03%)	(0.02%)	2.03	0.0282	0.38
Z (BATS)	(2.83%)	(1.72%)	3.06	(3.35%)	(1.69%)	(0.43%)	(8.93%)	80.20	0.0236	16.80
Total	168,853,115	853,404,234	5.05	116,936,966	51,498,723	417,426	594,167,624	159.70	0.0253	61.31

Note: This table presents the transactions, trading volumes, quoted prices and quoted sizes of SPYs on twelve 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), the Philadelphia Stock Exchange (X), and the BATS Exchange (Z). 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 SPYs. This study defines small trades as those consisting of 1–499 shares, medium-sized trades as 500–9999 shares, and large (block) trades as 10,000 shares or greater. The quoted depth (*Depth*) is calculated as ($Q_{bid} + Q_{ask}$), the quoted spread (*SP*) is calculated as $[(P_{ask} - P_{bid})/P_{mid}]$, and the market quality index (*MQI*) is calculated as $[Depth/2/100]/[SP \times 100]$, where Q_{ask} is the depth at ask, Q_{bid} denotes the depth at bid, P_{ask} is the ask price, P_{bid} represents the bid price, and P_{mid} is the midpoint of the bid and ask prices of the quotes.

References

Amihud, Y., & Mendelson, H. (1987). Trading mechanism and stock returns: An empirical investigation. *Journal of Finance, 42*, 533–553.

Ates, A., & Wang, G. H. K. (2005). Information transmission in electronic versus open-outcry trading systems: An analysis of US equity index futures markets. *Journal of Futures Markets, 25*, 679–715.

Baillie, R. T., Booth, G. G., Tse, Y., & Zabotina, T. (2002). Price discovery and common factor models. *Journal of Financial Markets, 5*, 309–321.

Barclay, M. J., & Warner, J. B. (1993). Stealth and volatility: Which trades move prices? *Journal of Financial Economics, 34*, 281–306.

Ben-David, I., Franzoni, F., & Moussawi, R. (2012). *ETFs, arbitrage, and contagion*Ohio State University Working Paper.

Ben-David, I., Franzoni, F., & Moussawi, R. (2014). *Do ETFs increase stock volatility?*Ohio State University Working Paper.

Ben-David, I., Franzoni, F., & Moussawi, R. (2017). Exchange-traded funds. *Annual Review of Financial Economics, 9*, 169–189.

Boehmer, B., & Boehmer, E. (2003). Trading your neighbor's ETFs: Competition of fragmentation? *Journal of Banking and Finance, 27*, 1667–1703.

Bollen, N. P. B., & Whaley, R. E. (1998). Are "Teenies" better? *Journal of Portfolio Management, 25*, 10–24.

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007–2008. *Journal of Economic Perspectives, 23*, 77–100.

Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies, 22*, 2201–2238.

Cespa, G., & Foucault, T. (2014). Illiquidity contagion and liquidity crashes. *Review of Financial Studies, 27*, 1615–1660.

Chakravarty, S. (2001). Stealth-trading: Which traders' trades move stock prices? *Journal of Financial Economics, 61*, 289–307.

Chakravarty, S., Gulen, H., & Mayhew, S. (2004). Informed trading in stock and option markets. *Journal of Finance, 59*, 1235–1257.

Chen, W.-P., & Chung, H. (2012). Has the introduction of S&P 500 ETF options led to improvements in price discovery of SPDRs? *Journal of Futures Markets, 32*, 683–711.

Chen, W.-P., Chung, H., & Lien, D. (2016). Price discovery in the S&P 500 index derivatives markets. *International Review of Economics and Finance, 45*, 438–452.

Cheng, L., & White, J. (2003). Measuring pricing inefficiencies under stressful market conditions. *Journal of Business Finance and Accounting, 30*, 383–411.

Chiu, J., Chung, H., Ho, K.-Y., & Wang, G. (2012). Funding liquidity and equity liquidity in the subprime crisis period: Evidence from ETFs markets. *Journal of Banking*

and Finance, 36, 2660–2671.
Chordia, T., Roll, R., & Subrahmanyam, A. (2011). Recent trends in trading activity and market quality. *Journal of Financial Economics, 101*, 243–263.
Chu, Q. C., Hsieh, W. G., & Tse, Y. (1999). Price discovery on the S&P 500 index markets: An analysis of spot index, index futures and SPDRs. *International Review of Financial Analysis, 8*, 21–34.
Chung, K. H., & Chuwonganant, C. (2012). Regulation NMS and market quality. *Financial Management, 41*, 285–317.
de Jong, F. (2002). Measures of contributions to price discovery: A comparison. *Journal of Financial Markets, 5*, 323–327.
Goldstein, I., Li, Y., & Yang, L. (2014). Speculation and hedging in segmented markets. *Review of Financial Studies, 27*, 881–922.
Gonzalo, J., & Granger, C. W. J. (1995). Estimation of common long-memory components in cointegrated systems. *Journal of Business and Economic Statistics, 13*, 27–35.
Goyenko, R. Y., & Ukhov, A. D. (2009). Stock and bond market liquidity: A long-run empirical analysis. *Journal of Financial and Quantitative Analysis, 44*, 189–212.
Grossman, S. F., & Miller, M. H. (1988). Liquidity and market structure. *Journal of Finance, 43*, 617–633.
Hameed, A., Kang, W., & Viswanathan, S. (2010). Stock market declines and liquidity. *Journal of Finance, 65*, 257–293.
Hasbrouck, J. (1995). One security, many markets: Determining the contributions to price discovery. *Journal of Finance, 50*, 1175–1199.
Hasbrouck, J. (2003). Intraday price formation in U.S. equity index markets. *Journal of Finance, 58*, 2375–2399.
Hendershott, T., & Jones, C. M. (2005a). Island goes dark: Transparency, fragmentation and regulation. *Review of Financial Studies, 18*, 743–793.
Hendershott, T., & Jones, C. M. (2005b). Trade-through prohibitions and market quality. *Journal of Financial Markets, 8*, 1–23.
Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *Journal of Finance, 66*, 1–33.
Krause, T., Ehsani, S., & Lien, D. (2014). Exchange-traded funds, liquidity and volatility. *Applied Financial Economics, 24*(24), 1617–1630.
Kurov, A., & Lasser, D. J. (2004). Price dynamics in the regular and E-mini futures markets. *Journal of Financial and Quantitative Analysis, 39*, 365–384.
Kyle, A. S., & Xiong, W. (2001). Contagion as a wealth effect. *Journal of Finance, 56*, 1401–1440.
Lien, D., & Shrestha, K. (2009). A new information share measure. *Journal of Futures Markets, 29*, 377–395.
Lien, D., & Wang, Z. (2016). Estimation of market information shares: A comparison. *Journal of Futures Markets, 36*, 1108–1124.
McInish, T. H., & Wood, R. A. (1992). An analysis of intraday patterns in bid–ask spread for NYSE stocks. *Journal of Finance, 47*, 753–764.
Nguyen, V., Van Ness, B. F., & Van Ness, R. R. (2007). Inter-market competition for exchange traded funds. *Journal of Economic and Finance, 31*, 251–267.
O'Hara, M. (2003). Presidential address: Liquidity and price discovery. *Journal of Finance, 58*, 1335–1354.
Pan, K., & Zeng, Y. (2016). *ETF arbitrage under liquidity mismatch*Harvard University Working Paper.
Parkinson, M. (1980). The extreme value method for estimating the variance in the rate of return. *Journal of Business, 53*, 61–65.
Stock, J., & Watson, M. (1988). Testing for common trends. *Journal of the American Statistical Association, 83*, 1097–1107.
Sultan, S. G., & Zivot, E. (2015). *Price discovery share-an order invariant measure of price discovery with application to exchange-traded funds*Department of Economics, University of Washington Working Paper.
Tse, Y., Bandyopadhyay, P., & Shen, Y.-P. (2006). Intraday price discovery in the DJIA index markets. *Journal of Business Finance and Accounting, 33*, 1572–1585.
Tse, Y., & Erenburg, G. (2003). Competition for order flow, market quality and price discovery in the NASDAQ 100 index tracking stock. *Journal of Financial Research, 26*, 301–318.
Tse, Y., & Hackard, J. C. (2004). Can Island provide liquidity and price discovery in the dark? *Review of Quantitative Finance and Accounting, 23*, 149–166.
Wang, G. H. K., Michalski, R. J., Jordan, J. V., & Moriarty, E. J. (1994). An intraday analysis of bid-ask spreads and price volatility in the S&P 500 index futures market. *Journal of Futures Markets, 14*, 837–859.