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期貨未平倉量的資訊內涵及其交易活動之研究

The Information Content of Futures Open Interest and Its Relation to Trading Activities

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摘 要

本研究分析台灣股價指期貨未平倉量的資訊內涵，結果顯示未平倉量可反映市場參與程度、避險需求、與投資人意見分歧三種資訊內涵。未平倉量增加伴隨市場流動性提升，包括成交量、市場深度、與市場衝擊成本皆隨未平倉量增加而顯著改善，此發現顯示未平倉量具有詮釋市場參與程度的資訊內涵。實證也發現未平倉量與現貨波動性顯著同方向變動，代表未平倉量可反映市場風險增大時投資人的額外避險需求。此外，未平倉量之增量和減量對成交量影響不同，對買賣方市場深度之差也有不對稱的影響，此發現符合未平倉量可反映投資人意見分歧的隱含意義。

【關鍵字】未平倉量、資訊內涵、市場流動性

Abstract

This study investigates the information content of open interest, using the index futures traded on the Taiwan market. We find that open interest reflects market participation, hedging demand and divergences in traders' opinions. Evidence shows that increases in open interest are accompanied by greater trading volume, larger depth, and lower market impact costs, indicating that higher open interest represent more market participation, which enhances liquidity. The hedging demand hypothesis is supported by the findings of significantly positive relationships between open interest and three spot volatility proxies. We also find asymmetric effect of upward versus downward open interest to trading volume, as well as to depth imbalance between buy- and sell-side of the order book. Results are consistent with the hypothesis that a large open interest signifies divergence in traders' opinions.

【Keywords】open interest, information content, market liquidity

1. Introduction

Open interest is the total number of positions for a derivatives contract that are "opened" and not yet liquidated by offsetting or fulfilled by delivery. Open interest can be calculated only for contractual instruments, mostly derivatives, but for spot assets. Each open interest is formed by a long (buy) position and a short (sell) position, matched through the trading process. For instance, the open interest of the Taiwan Stock Exchange Capitalization Weighted Stock Index Futures (TAIEX Futures; TX) on January 6, 2005 was 47,188, representing 47,188 long positions and 47,188 short positions at the end of that day.

Open interest is used extensively in academic literature as a proxy of market liquidity (Bessembinder and Seguin, 1992), market depth (Bessembinder and Seguin, 1993; Ragunathan and Peker, 1997; Watanabe, 2001), trading (hedging) demand (Chen, Cuny, and Haugen, 1995; Chang, Chou, and Nelling, 2000; Pan, Liu, and Roth, 2003), the difference in traders' opinions (Bessembinder, Chan, and Seguin, 1996), or investors' trading opinions for political elections (Chen and Tang, 2009). It is amazing that a single variable is interpreted in so many different ways and serve for so many purposes. However, studies rarely provide justification for the appropriateness of using open interest as the proxies it is claimed to be. As a result, there is lack of consensus regarding the information content of open interest. It is of our interest to clarify, at least, some information contents of open interest.

Open interest is found to be empirically related to volatility in many studies, but the interpretations were far from unanimous. Figlewski (1981) views open interest as market size and reports positive relationship between open interest and spot volatility. Chen et al. (1995) and Chang et al. (2000) argue that open interest represents demand for hedging. They postulate a positive relationship between open interest and spot market volatility. On the other hand, Bessembinder and Seguin (1992, 1993), Watanabe (2001), Ripple and Moosa (2009) suggest that open interest should be a proxy for liquidity or market depth, thus is negatively related to futures volatility.

A number of studies emphasize the predictability of open interest to other economic variables. For instance, Girma and Mougoue (2002), Yang, Bessler, and Fung (2004), and Yen and Chen (2010), respectively, test the predictability of open interest to futures spreads volatility, futures price and future volatility. Hong and Yogo (2010) assert that open interest, as a proxy of capital inflows of commodity futures, predict commodity returns. In addition, they find that open interest forecasts macroeconomic variables such as inflation and bond return in long term. The multiple uses of open interest undoubtedly make it interesting, however, increase the confusion with respect to its true information role. Motivated by the multi-purposed usages of open interest, this study focuses on what open interest itself reflects, in an attempt to provide more comprehensive understanding about the original information of open interest under different market situations.

In addition to the academic attention, open interest is often used by practitioners for technical analysis in derivatives trading. A classical example of such usage can be found in Shaleen (1991) and Pring (2002), who forecast market price trend using parallel open interest, trading volume and transaction price. However, when it comes to the interpretation of open interest, practitioners sometimes apply the technical analysis rules derived for trading volume without discriminating the difference between open interest and trading volume.[1] The approach, though convenient, overlooks the obvious fact that change in open interest is not always accompanied by the same direction and amount of volume change.[2] Motivated by the common uses (or misuses) of the open interest information, this study provides evidence that clarify the information contents of open interest.

The current study analyzes the open interest of the TAIEX index futures contracts (TX). The contract uses the value-weighted Taiwan Stock Exchange Index that consists of almost all listed stocks (around 800 stocks) on the Taiwan Stock Exchange as the underlying index. The TAIEX futures contract began to be listed in the Taiwan Futures Exchange (TAIFEX) since July 21, 1998. The exchange offers quarterly contracts expired in March, June, September, and December, begin to trade nine months before expiration, plus monthly contracts for every remaining months, begin to trade two months prior to expiration. The TAIFEX operates an electronic order-driven trading system (ETS). The ETS matches, in a continuous manner, incoming market and limit orders in price and time priority rules that maximize trading volume. Trade results are instantaneously disseminated to the crowd. The disseminated information include traded price, trading volume, the best five bid and ask prices, and the number of limited orders remaining on the order book for the best five ticks. Open interest as of the end of day is reported after a regular trading session.

1 Generally, the practitioners' reports do not provide clear explanation to open interest. They often view open interest and trading volume similar variables and apply the same filter rules to both variables (Liou, 2004; The Investment Blog, 2008).

2 Transactions always increase volume but not necessary open interest. When both sides (long and short) in a matched trade open new positions, the open interest increases. When both sides use the trade to offset their opened positions, open interest is reduced. When one side open but the other side offset, the open interest is left unchanged. Therefore, open interest could increase or decrease with volume due to transactions. Open interest decline substantially, accompanied by large volume, when traders decide to exit the market altogether. An example of such occasion is when a contract approaches to expiration.

The TAIFEX market structure differs from other developed markets in that transactions are mostly contributed by retail traders. According to a statistical report on the TAIFEX website, individual investors accounted for 85.49% of trading volume on January 2003, whereas all institutional investors shared the remaining 15%. Retail traders are mostly short-term speculators but rarely hedgers who hold futures positions for long. In addition, the divergence/convergence in retail traders' opinions would be different from that of institutional traders. If open interest reflects the hedging demand as suggested by Chen et al. (1995) or the divergence in traders' opinions as in Bessembinder et al. (1996), the unique market structure could have resulted in very different information contents of open interest in Taiwan than in other markets. Kuo, Hsu, and Chiang (2005) study the Taiwan futures market and show that the increase in expected open interest (viewed as market depth) does not significantly mitigate volatility. Their results are not consistent with Chou and Wang (2006), who find that open interest has a significantly negative impact on price volatility after the tax reduction. This paper provides additional evidence on the informational contents of open interest for Taiwan futures markets.

In next section, we construct three hypotheses regarding the information contents of open interest, based upon existing literature. We provide data description and empirical models in Section 3. In the fourth section, we present the empirical results for each hypothesis. The last section concludes the paper.

2. Literature Background and Hypothesis Development

In this section, we develop three hypotheses and related implications to investigate the information content of futures open interest. These hypotheses are generated through the analysis of existing literature. We then develop testable implications under each hypothesis.

2.1 Market Participation

Hypothesis 1: Open interest reflects the participation of traders.

Based on the definition and the calculation of open interest, it represents the total number of futures contracts that remains open and the amount of capital already flowed into the futures market. Open interest is arguably an appropriate measure of current participant activity, which is determined endogenously in the futures markets (Chang et al., 2000). If open interest indeed reflects market participation, we would observe a close association between open interest and liquidity measures, because more participation in trading usually lead to better liquidity.

Liquidity is defined as the price of immediacy (O'Hara, 1995), the price impact from large trade (Amihud, 2002), or the ability to convert assets into cash instantaneously (Lippman and McCall, 1986) at the lowest transaction costs (Harris, 1990). It is easier to define but far more difficult to measure. Most of the literature views volume, market depth, bid-ask spreads and price impact as proxies for market liquidity. Since there is no consensus about the best measure, we employ four common liquidity proxies: trading volume, depth, the Amihud illiquidity measure, and the Amivest liquidity ratio.

Empirical studies have reported that open interest is positively related to trading volume, a convenient proxy of liquidity. For instance, Martell and Wolf (1987), in investigating the determinants of trading volume in metal futures, find that open interest has a significantly positive explanation for trading volume. Moser (1994) reports that the coefficient of elasticity between open interest and volume of S&P 500 index futures is positive and the coefficient increases substantially after the Black Monday crash of October 19, 1987.[3]

Market depth is usually viewed as the proxy of liquidity in empirical evidence, this can be seen in Lee, Mucklow, and Ready (1993) and Brockman and Chung (1999). In a deeper market, market orders, which seek for immediate transaction, are matched with higher probability, fast speed, and smaller market impact costs. Therefore, market depth should be a proxy of liquidity and participation.

Goyenko, Holden, and Trzcinka (2009) suggest that the illiquidity ratio provided by Amihud (2002) does well in measuring price impact thus is a high quality liquidity proxy based on daily data. Furthermore, the Amivest liquidity ratio is also a daily measure of price impact long adopted by academics and practitioners. Hence, we utilize four liquidity metrics: volume, depths, the Amihud illiquidity ratio and the Amivest liquidity ratio.[4]

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3 Open interest may co-move with futures trading volume because of the two variables share the same cyclical pattern of futures contracts. That is, open interest and volume of a contract increase as the contract about to become the nearby contract. Both decrease sharply when the futures contract approaches it maturity (Kolb and Overdahl, 2006). To investigate the association between open interest and volume independently to the cyclical pattern, this study remove the cyclical pattern in open interest (and volume) by aggregating the open interest in the two near-month contracts. See section 3.1 for detail.

4 It should be noted, the quoted bid-ask spread may not be an appropriate liquidity proxy for the TAIEX futures contracts. This is because that the TAIEX index futures is so liquid that the bid-ask spreads are constantly as low as the minimum tick. As a result, the bid-ask spreads are insensitive to the changes in liquidity.

If open interest reflects participation in the futures markets, a greater open interest should be accompanied by better market liquidity, which can be measured by larger volume, more depth, and smaller market impact costs. Our first testable implication is constructed as follows:

Testable implication (1): Open interest is positively associated with various liquidity measures.

Bessembinder and Seguin (1993) partition open interest into expected and unexpected components using multivariate forecasting methods. The expected open interest primarily reflects the level at the beginning of one day, and the unexpected open interest captures the change in open interest due to unanticipated information impacts over the day. In addition, they assert that the unexpected change in open interest is a proxy for the current willingness of futures traders to risk capital by providing depths. In an order-driven market like TAIFEX, market depths come from limit orders submitted for better prices, which could quantify the willingness of liquidity provision by market participants. If open interest indeed represents participation, its unexpected component would be positively associated with liquidity provision that proxies for the willingness to bear risk to participate in the market. Based on the argument of Bessembinder and Seguin (1993), the second testable implication is constructed as follows:

Testable implication (2): Unexpected open interest is positively associated with certain liquidity measures, particularly depth.

2.2 Hedging Demand

Hypothesis 2: Open interest reflects hedging demand.

One primary function of futures markets is to facilitate hedging against spot market volatility. As stock volatility surges, there is increasing hedging demand using index futures. Open interest in index futures increases as more hedgers enter and hold positions. Bessembinder and Seguin (1993) suggest that many speculators are "day traders" who do not hold open positions overnight, and hence their trading does not increase open interest. Consequently, the changes in open interest primarily represent the rise and fall of hedgers' demand (Lucia and Pardo, 2010; Aguenaou, Gwilym, and Rhodes, 2011). The above argument suggests that open interest in futures contracts reflect hedging demand on the spot market.

Literature has viewed aggregate open interest a proxy for trading demand for all participants. Pan et al. (2003) suggest that an increase in price volatility induces both hedgers and speculators to engage in more futures trading. In particular, when spot price volatility goes up, trading demand for hedgers, not for speculators, will increase significantly. Chang et al. (2000) assert that increasing spot volatility tends to increase the demand for hedging more than the demand for speculation. If open interest indeed reflects hedging demand, it would rise and fall with the spot volatility, which stimulate hedging transactions. This leads our testable implication (3) as follows:

Testable implication (3): Open interest is positively associated with spot volatility.

Chang et al. (2000) further suggest that if volatility shock arises during the day, hedgers will adjust upward their expected volatility for the next term. Given the expected volatility at the beginning of the day, the unexpected volatility shock will drive further portfolio adjustment and additional hedging demand. This implies that the increase in unexpected volatility should correspond to higher level of open interest, reflecting the increase in hedging demand. Our testable implication (4) thus is constructed as follows:

Testable implication (4): Open interest rises with increased unexpected spot volatility.

2.3 Divergences in Traders' Opinions

Hypothesis 3: Open interest represents the cross-sectional divergence in opinions regarding the future value of the underlying asset.

Previous literature has long viewed volume as the outcome of differences in traders' opinions. Volume increase significantly when investors hold diverged expectations (Varian, 1985) or interpret the available information differently (Harris and Raviv, 1993; Shalen, 1993). Bessembinder et al. (1996) emphasize that open interest also varies with the divergence of traders' opinions. They argue that the difference of opinion about the future price could induce trading, particular the open-position transactions that increases open interest. When traders are divergence in their opinions, those who anticipate the price to rise rush to open-buy transactions (open new positions to long) while those who anticipate the price to fall engage in open-sell transactions (open new positions to short). Together their transactions increase open interest and volume simultaneously. As a result, whenever the increment in open interest is accompanied by greater volume, the change in open interest is likely due to the divergences of opinion.

On the other hand, when traders are less divergence in their views about future equilibrium price, the current price will quickly move toward the equilibrium without triggering significant amount of transactions. As opinions converge and prices move toward equilibrium, speculators are no longer interest in holding positions. They tend to close exiting positions via off-setting transactions. In such cases, open interest decreases without discernible volume activity.

According to above discussion, if open interest and volume are both the outcome of divergence in opinion, we will observe a positive association between open interest and volume. When opinions converge, we will observe decrease in open interest with less significant volume changes. The testable implication (5) in Hypothesis 3 is stated as follows:

Testable implication (5): Increases in open interest are associated with significantly larger volumes but decreases in open interest have smaller impact on trading volume.

Hypothesis 3 states that open interest represents divergence in opinion. Here we propose using the "difference between buy versus sell orders" as a proxy for measuring the degree of divergence/convergence in traders' outlook. When a divergence of opinion occurs, traders who predict a higher equilibrium price submit buy orders while traders who predict a lower equilibrium price submit sell orders. As a result, limit orders on bid and ask sides of the market become more symmetrical. In contrast, when opinion converges, limit orders tend to concentrate on only one side of the market (either bid or ask), as most traders agree with the direction of price changes and bet on the same side all together. In this sense, we can reasonably use the difference in buy versus sell depths as a proxy for the divergence in opinion: a large difference indicates convergence in opinion whereas a symmetric buy and sell depth represents divergence in opinion. If open interest reflects divergence in opinion, it is likely to observe higher open interest associated with more equality in buy and sell orders. Therefore, the testable implication (6) in Hypothesis 3 is as follows:

Testable implication (6): Open interest increases with the degree of symmetry in bid and ask depths.

3. Empirical Model and Data

3.1 Data

This study uses data of Taiwan Exchange Stock Index Futures (TAIEX) for the period from January 2003 to December 2011, a total of 2,226 trading days. We obtain daily open interest, daily trading volume and intraday order size on the best five bid and ask prices. We also extract daily high, low, opening and closing prices of the TAIEX spot index for later calculation of the spot volatility variables. All data are provided by the TEJ (Taiwan

Economic Journal) database. The following procedures are adopted to calculate the variables needed for the analysis.

(1) We calculate the series of daily open interest values (*OI*) by summing the open interest across two near-month contracts.[5] For example, the open interest on April 1, 2003, is the sum of open interest of two index futures contracts (with expiration days in April and May) on that day. The cross-sectionally aggregated open interest of two near-month contracts provides at least two benefits over the process of rolling over open interest of single contract. First, the sum of open interest across two near-month contracts effectively removes the cyclical pattern of open interest associated with the life of an individual contract. Second, the aggregated open interest incorporates hedge or speculative purposed trading using the deferred contracts. We calculate the daily time series of volume (*VOL*) and depth measures (*DEP*) applying similar methodology by aggregating the two near-month contracts.

Table 1 presents the summarize statistics for the daily volume and open interest series of nearby contract alone versus the aggregation of two near-month contracts. Both series are normalized by the value of the all traded contracts. The mean of nearby ratio in volume and open interest is 92.5% and 83.05%, with a high standard deviation (14.43% and 17.28%). However, the two-near-month ratio for volume and open interest rises to over 95%, showing that trading activity almost concentrates on two near-month contracts. More importantly, the two-near-month ratio has very low standard deviations (0.0353%) relative to that of nearby contract. This indicates that the series have alleviated the noticeable life-cycle volatility in the individual nearby contracts.

Table 1 Proportion of Volume and Open Interest

Variables	Volume		Open Interest	
	Nearby (%)	Two-near-month (%)	Nearby (%)	Two-near-month (%)
Mean	92.55	99.76	83.05	95.32
Median	98.35	99.85	88.55	96.01
Std. dev.	14.43	0.0033	17.28	0.0353
Max.	99.94	1	99.49	99.77
Min.	20.34	94	16.98	80.91
No. Obs.	2,226	2,226	2,226	2,226

Note: The table summarizes the daily series of the volume and open interest for nearby contract and the sum of two nearest-month contracts as proportion of all traded contracts.

5 We thank an anonymous referee for suggesting the use of the sum of the two nearest month contracts.

(2) We follow the method proposed by Bessembinder and Seguin (1993) to decompose open interest (*OI*) into its expected and unexpected components using an ARIMA [(1,3,19,20,21), 0, (3,24,26,39,44)] process (see Appendix A). The expected open interest (*EOI*) is the fitted value of the ARIMA model, while the unexpected open interest (*UOI*) is the difference between the actual open interest (*OI*) and expected open interest (*EOI*). The expected portion represents the normal level of open interest measured by the time series model, while the unexpected portion captures the change or innovation of open interest beyond the prediction of the model.

(3) We calculate the market depth, *DEP*, by summing the order size on the best five bid and ask prices on the limit order book. Daily market depth is the weighted average of the intraday depths, where the weight is the elapsed time of each intraday depth record.

(4) For volatility variables, Garman and Klass (1980) assert that the daily price ranges contain more information about volatility, comparing to the volatility calculated from closing prices only. We therefore select three volatility estimators using the full range of daily prices proposed by Parkinson (1980), Garman and Klass (1980) (*GK*), and Rogers and Satchell (1991) (*RS*).[6] All of them are decomposed into their expected and unexpected components using the Box-Jenkins ARIMA model suggested by Bessembinder and Seguin (1993), the same technique used for decomposing the open interest. They are separately identified as the ARIMA [(1,4,9,10), 0, (1,4,25,26)], ARIMA [(2,7,15), 0, (1,2,5,17,25,27,33)] and ARIMA [(1,12,15), 0, (2,17,25,32)] processes (see Appendix B). The residuals of the ARIMA model are the unexpected component of volatility, and the differences between the actual volatility and residuals are the expected volatility.

3.2 Empirical Models

We employ multiple regression analysis to test the three hypotheses about the information contents of open interest. We construct eight models to verify every implication

6 The Parkinson, GK and RS volatility proposed by Parkinson (1980), Garman and Klass (1980) and Rogers and Satchell (1991), respectively, are given in below:

$$Parkinson_t = [\ln(\frac{H}{L})^2/4\ln(4)]\times 10^6$$

$$GK_t = [0.5\times\ln(\frac{H}{L})^2 - (2\ln(2)-1)\times\ln(\frac{O}{C})^2]\times 10^6$$

$$RS_t = [\ln(\frac{H}{C})\times\ln(\frac{H}{O}) + \ln(\frac{L}{C})\times\ln(\frac{L}{O})]\times 10^6$$

where H, L, C, and O are the highest price, the lowest price, the closing price and the opening price, respectively, on a daily basis. They are multiplied by 10^6 for adjustments of scale.

of the hypotheses and to analyze the relationship between open interest and other variables.

Models (1) and (2) test implications (1) and (2) of Hypothesis 1, which states that open interest reflects market participation. We regress liquidity measures, proxied for the degree of market participation, against open interest and other control variables.

$$Liq_t = \alpha_1 + \beta_1 OI_t + \delta_1 DEP_t + \eta_1 VOL_t + \gamma_1 TTM_t + \sum_{j=1}^{4} \kappa_{1,j} D_{t,j} + \varepsilon_t \tag{1}$$

$$Liq_t = \alpha_2 + \beta_2 EOI_t + \varphi_2 UOI_t + \delta_2 DEP_t + \eta_2 VOL_t + \gamma_2 TTM_t + \sum_{j=1}^{4} \kappa_{2,j} D_{t,j} + \varepsilon_t \tag{2}$$

where *Liq* is one of the four liquidity proxies including volume (*VOL*), depth (*DEP*), the Amihud illiquidity ratio (*ILLIQ*) and the Amivest liquidity ratio (*Amivest*). The illiquidity ratio offered by Amihud (2002) is the daily ratio of absolute value of futures return to volume, i.e., $ILLIQ = |Return|/VOL$. It measures the price impact associated with per trading volume. The larger the *ILLIQ*, the greater is the impact of a given amount of trading and the lesser is market liquidity, and the less the market liquidity. The Amivest liquidity ratio measures volume per unit of absolute value of price return, i.e., $Amivest = VOL/|Return|$, and was used by Dubofsky and Groth (1984), Cooper, Groth, and Avera (1985), and Amihud, Mendelson, and Lauterbach (1997).[7] A high Amivest ratio indicates that futures contracts are traded with little change in price, and hence liquidity is more sufficient.

For explanatory variables in Model (1), *OI* is the sum of open interest in two near-month contracts on day t. We include *DEP* and *VOL* as control variables for regressions that do not use them as dependent variable. This allows us to observe the net effect of *OI* to the *Liq* variable while control for potential omitted variable bias induced by *DEP* and/or *VOL*. We also incorporate *TTM*, the remaining days to expiration of the contract with the greatest open interest, to further control for the cyclical pattern in the open interest series. We add four daily dummy variables D_j, j = 1, 2, 3, 4 for Monday, Tuesday, Thursday and Friday to control for the day-of-the-week effect.

A positive (negative) value of β_1 for regressions using *VOL*, *DEP*, and *Amivest* (*ILLQ*) as dependent variable indicates that the level of open interest changes with liquidity, indicating that open interest reflects information content of market participation. The results

7 For the calculation of Amihud illiquidity ratio and the Amivest liquidity ratio, we follow Amihud et al. (1997) by employing volume instead of dollar volume.

would be consistent with implication (1) in Hypothesis 1.

We use Model (2) to test implication (2) that the "unexpected" component co-moves with liquidity measures, particularly the depth measure. *EOI* and *UOI* in equation (2) are, respectively, expected and unexpected open interest, decomposed from *OI* by the ARIMA model as described in section 3.1. If φ_2, the coefficient of depth, for *DEP* regression is significantly positive, the evidence would support implication (2) in Hypothesis 1.

Hypothesis 2 generates implications about the relationship between open interest and spot market volatility. To test the implication (3), we regress the expected open interest against proxies of spot index volatility in Model (3) and the unexpected open interest against the spot volatility in Model (4). The regression models are specified as:

$$EOI_t = \alpha_3 + \beta_3\sigma_t + \gamma_3 TTM_t + \sum_{j=1}^{4}\kappa_{3,j}D_{t,j} + \varepsilon_t \tag{3}$$

$$UOI_t = \alpha_4 + \beta_4\sigma_t + \gamma_4 TTM_t + \sum_{j=1}^{4}\kappa_{4,j}D_{t,j} + \varepsilon_t \tag{4}$$

where *EOI* and *UOI*, respectively, stand for expected and unexpected component of open interest. For spot market volatility (σ_t), we apply measures developed by Parkinson (1980), Garman and Klass (1980) and Rogers and Satchell (1991), respectively and perform regression for each volatility measure independently (See footnote 7 for the definition of the three volatility measures). Both Model (3) and (4) include days to expiration (*TTM*) and day-of-week dummies (D_j) as control variables. The finding of positive and significant β_3 and β_4 supports the positive association between open interest and spot market volatility predicted by implication (3).

Implication (4) stresses that open interest increases with unexpected volatility. To test it, we perform similar regressions to Model (3) and (4) but separate the spot volatility into expected volatility and unexpected volatility.

$$EOI_t = \alpha_5 + \beta_5\sigma_t^{expected} + \varphi_5\sigma_t^{unexpected} + \gamma_5 TTM_t + \sum_{j=1}^{4}\kappa_{5,j}D_{t,j} + \varepsilon_t \tag{5}$$

$$UOI_t = \alpha_6 + \beta_6\sigma_t^{expected} + \varphi_6\sigma_t^{unexpected} + \gamma_6 TTM_t + \sum_{j=1}^{4}\kappa_{6,j}D_{t,j} + \varepsilon_t \tag{6}$$

where $\sigma_t^{expected}$ and $\sigma_t^{unexpected}$ respectively stand for the expected and unexpected component of spot index volatility. We calculate the three volatility measures developed by Parkinson (1980), Garman and Klass (1980), and Rogers and Satchell (1991) and perform regression using each measure as explanatory variable. For each spot volatility measure, we partition it into the expected and unexpected volatilities using ARIMA model as described in section 3.1. Remaining variables are defined as previously. The findings of positive and significant φ_5 and/or φ_6 corresponds to implication (4), that the unexpected spot volatility affects open interest, and is consistent with the hypothesis that open interest reflects hedging demand.

Finally, we construct Model (7) and Model (8) to test implications (5) and (6) of Hypothesis 3 that open interest reflects differences of opinion. Model (7) resembles the empirical model in Bessembinder et al. (1996), designed to test the influence of the variation in open interest on trading volume (*VOL*).

$$VOL_t = \alpha_7 + \sum_{i=1}^{2} \beta_{7i}\, DiOI_i \left|\Delta OI_t\right| + \theta_7 EOI_t + \eta_7 UOI_t + \varphi_7 DEP_t + \gamma_7 TTM_t + \sum_{j=1}^{4} \kappa_{7j} D_j + \varepsilon_{7t} \qquad (7)$$

where $|\Delta OI|$ measure the absolute change of open interest. To separately measure the impact of increment and decrement in open interest on volume, we follow Bessembinder et al. (1996) by using the unsigned change in open interest ($|\Delta OI|$), and multiplied by two dummy variables ($DiOI_i$, $I = 1,2$) for cases of upward and downward *OI* movement. This allows us to model the asymmetrical impacts on the volume. If open interest increases (i.e., $\Delta OI > 0$), the first dummy ($DiOI_1$) equals one and the second dummy ($DiOI_2$) equals zero. If open interest falls (i.e., $\Delta OI < 0$), the second dummy ($DiOI_2$) equals one and the first dummy ($DiOI_1$) equals zero. So β_{71}, the coefficient of $DiOI_1|\Delta OI|$, represents the impact from the *increment* in open interest on volume, whereas β_{72}, the coefficient of $DiOI_2|\Delta OI|$, represents the impact from the *decrement* in open interest on volume. Implication (5) predicts an asymmetric influence on volume from upward *OI* versus downward *OI*. The finding of greater β_{71} than β_{72}, that is, the positive impact on volume due to open interest increments is greater than the negative impact due to open interest decrements, supports the implication.

In Model (7), we use expected open interest (*EOI*), unexpected open interest (*UOI*), market depth (*DEP*), *TTM* and dummies for the day-of-the-week effect as control variables.[8] All control variables are defined as previously.

8 We thank an anonymous referee for suggesting that the independent variables used in Hypothesis 1 should be controlled in Hypothesis 3, and vice versa.

According to implication (6), increases in open interest are associated with symmetrical increase in the bid and ask depth. This study uses Model (8) to test the relationship between open interest and market depth, using *VOL*, *EOI*, *UOI*, *TTM* and dummies of the day-of-the-week as control variables. Model (8) examines the association between changes in open interest and the symmetricity in bid and ask depth. The model is specified as:

$$\left|BDEP_t - ADEP_t\right| = \alpha_8 + \sum_{i=1}^{2}\beta_{8i} DiOI_i \left|\Delta OI_t\right| + \theta_8 EOI_t + \eta_8 UOI_t + \varphi_8 VOL_t + \gamma_8 TTM_t + \sum_{j=1}^{4}\kappa_{8j} D_j + \varepsilon_t \quad (8)$$

where $|BDEP - ADEP|$ is the absolute difference between the bid depth (*BDEP*) and ask depth (*ADEP*), measuring the extent to which the buy side liquidity provision differs from the sell side liquidity provision, or the depth imbalance. The greater depth imbalance (large $|BDEP - ADEP|$) indicates more convergence, or less divergence, in traders' opinions. Coefficients β_{81} and β_{82} respectively capture the effect of *OI* increase and *OI* decrease on the depth imbalance. According to implication (6), a divergence in opinions would lead to higher open interest and increased liquidity provision on both sides of the market, thus a smaller $|BDEP - ADEP|$. An inverse relationship (negative β_{81}) between increment of open interest and $|BDEP - ADEP|$ is consistent with implication (6). On the other hand, a convergence in opinions would lead to reduction in open interest (negative $|\Delta OI|$ and positive $DiOI_2|\Delta OI|$) and more asymmetric bid and ask depths (larger $|BDEP - ADEP|$). This predicts a positive β_{82} in Model (8).

4. Empirical Results

4.1 The Descriptive Statistics

Table 2 provides descriptive statistics for the variables. The open interest (*OI*) and expected open interest (*EOI*) are similar in terms of their statistics. This is not surprising because the *EOI* roughly reflects the expected open interest at the beginning of the trading day, which is approximately equal to yesterday's closing *OI* level. The unexpected open interest (*UOI*) is very different from the OI_t and EOI_t. The mean of the unexpected open interest is small (less than 1%) relative to that of the *OI* and *EOI*, however, its standard deviation exceeds one fourth of that of the *OI* and *EOI*. The substantial variation in *UOI* relative to its mean indicates that there could be rich information content in the series.

Table 2 Descriptive Statistics and Unit Root Tests

Variables	Open interest (,000)				Market depth (,000)			Volume (,000)
	OI	*EOI*	*UOI*	*|ΔOI|*	DEP (Bid+Ask)	Bid	Ask	
No. Obs.	2,226	2,205	2,205	2,225	2,226	2,226	2,226	2,226
Mean	47,631	47,807	138.82	2,097	323	161	162	63,668
Median	46,186	46,267	500	1,215	308	155	153	50,913
Std. dev.	15,429	14,967	3,701	3,217	140.09	70.84	72.27	39,349
Max.	90,765	89,539	12,475	31,192	1,046	519	700	289,303
Min.	11,636	12,098	-26,148	0	55	23	32	9,539
Skewness	0.20	0.21	-2.83	4.45	0.78	0.82	1.05	0.94
Kurtosis	2.62	2.58	17.14	27.67	3.93	4.19	5.51	3.70
Unit root tests								
ADF	-9.67[a]	-12.7[a]	-46.89[a]	-6.70[a]	-5.78[a]	-3.07	-5.31[a]	-6.38[a]
Lag number	0	18	0	24	4	14	6	9

Note: *OI* is the open interest, *EOI* is the expected component of open interest, *UOI* is the unexpected open interest, *|ΔOI|* is the absolute of open interest changes, and market depth is the sum of order size. All of open interest and volume variables are calculated using two near-month contracts. The null hypothesis of unit root is tested by the ADF test with a constant term, linear trend and lag terms suggested by the SBC. The table reports the t-statistics of ADF test, with superscript a, b and c indicating significance at the 1%, 5% and 10% confidence levels, respectively.

Summary statistics of market depths are reported in columns 6 through 8 of Table 2. The ask depth series resembles the bid depth series in the first two moments of the distribution, but with larger skewness and kurtosis. Since we do not distinguish the buy side and sell side depth, the bid + ask depth is used in subsequent analysis. Finally, the unit root tests in the last two rows in Table 2 suggest that each variable is a stationary series (i.e., *I*(0) series) except for the bid depth series. The ADF test in every variable rejects the null hypothesis of one unit root at a 10% significance level.

4.2 Test Results of Open Interest Reflecting Participation

Table 3 presents the test results for implications (1) and (2) of Hypothesis 1 using Model (1) and (2), respectively. For the results of Model (1), the level of open interest is positively related to trading volume (*VOL*), depth (*DEP*), and Amivest ratio (*Amivest*) and negatively associated with the Amihud illiquidity ratio (*ILLQ*). All coefficients of *OI* are statistically significant except the regression for Amivest ratio. Results suggest that the increase in open interest is accompanied by higher trading volume, greater depth provision, and smaller market impact costs. It supports the implication that open interest is positively associated with market liquidity. Results are consistent with the hypothesis that open interest reflects the participation of traders.

Table 3 Regressions of Liquidity Proxies on Open Interest of Index Futures

$$Liq_t = \alpha_1 + \beta_1 OI_t + \delta_1 DEP_t + \eta_1 VOL_t + \gamma_1 TTM_t + \sum_{j=1}^{4} \kappa_{1j} D_{t,j} + \varepsilon_t \tag{1}$$

$$Liq_t = \alpha_2 + \beta_2 EOI_t + \varphi_2 UOI_t + \delta_2 DEP_t + \eta_2 VOL_t + \gamma_2 TTM_t + \sum_{j=1}^{4} \kappa_{2,j} D_{t,j} + \varepsilon_t \tag{2}$$

Liquidity Proxies	Model (1)				Model (2)			
	VOL	*DEP*	*ILLQ*	*Amivest*	*VOL*	*DEP*	*ILLQ*	*Amivest*
Intercept (α)	-8,573[a]	361.50[a]	465.63[a]	-4,529	-8,533[a]	361.25[a]	465.57[a]	-4,513
	(-2.73)	(26.60)	(19.26)	(-0.65)	(-2.74)	(26.59)	(19.25)	(-0.65)
OI_t (β_1)	1.74[a]	0.0006[b]	-0.0032[a]	0.034				
	(45.45)	(2.43)	(-7.72)	(0.29)				
EOI_t (β_2)					1.776[a]	0.0006[c]	-0.0031[a]	0.0223
					(46.01)	(2.10)	(-7.47)	(0.19)
UOI_t (φ)					0.891[a]	0.0018[b]	-0.0038[b]	0.2104
					(5.47)	(2.17)	(-3.01)	(0.58)
DEP_t (δ)	-58.64[a]		-0.1099[a]	33.40[a]	-57.15[a]		-0.1094[a]	33.24[a]
	(-14.23)		(-3.32)	(3.51)	(-13.93)		(-3.30)	(3.49)
VOL_t (η)		-0.0015[a]	-0.0012[a]	0.3456[a]		-0.0014[a]	-0.0012[a]	0.348[a]
		(-14.23)	(-7.26)	(7.31)		(-13.93)	(-7.27)	(7.32)
TTM_t (γ)	426.77[a]	1.59[a]	-0.5613	-322.9[b]	356.80[a]	1.67[a]	-0.6112	-309[b]
	(6.90)	(5.13)	(-1.17)	(-2.34)	(5.68)	(5.32)	(-1.25)	(-2.20)
Monday (κ_1)	-2,204	-18.10[b]	-2.79	1,216	-2,511	-17.62[b]	-3.05	1,288
	(-1.23)	(-2.03)	(-0.20)	(0.31)	(-1.41)	(-1.97)	(-0.22)	(0.32)
Tuesday (κ_2)	-466	0.37	-14.63	2,158	-563.96	0.52	-14.71	2,180
	(-0.26)	(0.04)	(-1.08)	(0.55)	(-0.32)	(0.06)	(-1.08)	(0.56)
Thursday (κ_3)	2,977[b]	-0.85	-23.30[c]	-1,223	337.57	2.72	-25.31[c]	-670
	(1.69)	(-0.10)	(-1.72)	(-0.31)	(0.19)	(0.30)	(-1.80)	(-0.17)
Friday (κ_4)	1,067	-5.38	-4.62	-142.10	597.22	-4.75	-4.97	-45.21
	(0.60)	(-0.61)	(-0.34)	(-0.04)	(0.34)	(-0.54)	(-0.36)	(-0.01)
H_0: All $_{\kappa 1j}$ = 0	1.22	1.49	1.14	0.22	1.02	1.56	1.14	0.18
H_0: $\beta_2 = \phi_2$					7.30[a]	3.37[c]	0.01	0.48
Adj. R^2	0.5577	0.1366	0.1468	0.0464	0.5590	0.1376	0.1464	0.0462

Note: The OLS regression Model (1) and (2) examine the implications of Hypothesis 1 by regressing the proxies of liquidity variables on open interest. The dependent variables are VOL_t, (volume of the two nearest expiration futures contracts), DEP_t (market depth) $ILLQ_t$ (the Amihud (2002) illiquidity proxy), and $Amivest_t$ (the Amivest liquidity ratio). The primary independent variables of concern include OI_t (open interest,), EOI_t, (expected open interest) and UOI_t (unexpected open interest). OI_t is the open interest of the two nearest expiration futures contracts. EOI_t, and UOI_t are partitioned from OI_t using *ARIMA* model. TTM_t is the time-to-maturity (in days) of the futures contracts with the largest volume. D_j (j = 3, 4, 5, 6) are four daily dummies for the day-of-the-week effect. Both $ILLQ_t$ and $Amivest_t$ are multiplied by 1,000. Each H_0 is tested using the F-statistics. The superscript a, b, and c indicate significance at the 1%, 5% and 10% confidence levels, respectively.

Model (2) regresses the liquidity proxies against decomposed open interest. We find that the unexpected open interest (*UOI*) increases with volume (*VOL*), depth (*DEP*), and decreases with market impact (*ILLQ*). Note that the coefficient of *UOI* is positively significant at the 5% confidence levels for regression using depth (*DEP*) as a liquidity proxy. This relationship supports the view of Bessembinder and Seguin (1993) that *UOI* is a close proxy for the current willingness of futures traders to risk capital by providing depths. Moreover, the expected open interest positively associated with volume, depth, and Amivest liquidity ratio, and negatively correlated with the Amihud illiquidity measures. The result is consistent with the findings of Martell and Wolf (1987) and Moser (1994) that the cross-sectional aggregated open interest share similar information contents of trading volume and market depth.

In both Model (1) and (2), the *TTM*, time to maturity, is positively related to volume and depth. The day-of-the-week dummies, on the other hand, are rarely significant. Regression adjusted-R^2 enhanced after adding the control variables, namely volume (for dependent variable not volume) and/or depth (for dependent variable not depth). In sum, results are consistent with testable implications (1) and (2), and hence support the Hypothesis 1, that open interest reflects the participation of traders.

4.3 Test Results of Open Interest Reflecting Hedging Demand

Table 4 reports regression estimates for testable implications (3) of Hypothesis 2. We are interested in whether open interest changes with spot volatility, thus reflects demand for hedging. In Model (3), the coefficients of spot volatility are significantly positive at the 1% level, regardless which volatility proxy (*Parkinson*, *GK*, or *RS*) is used. It suggests that greater spot market volatility tends to induce increases in expected component of open interest. While the expected open interest positively move with index volatility, the unexpected open interest, on the other hand, does not correspond to spot volatility. In the three regressions of Model (4), none of the coefficient of spot volatility is statistically significant.[9] Evidence suggests that hedging demand stimulated by spot volatility is reflected only in the expected open interest. Our results are consistent with Chen et al. (1995), Chang et al. (2000) and Pan et al. (2003) that open interest can represent the hedging demand for futures contracts. All *TTM* variables are negatively correlated to open interest, indicating that the sum of open interest of the two nearby contracts has cyclical pattern.

In Table 5, we perform regressions that examine whether open interest increases with *unexpected* spot volatility, the implications (4) of Hypothesis 2. Note that in regression Models (5) and (6), the explanatory variables for spot volatility include both expected and *unexpected* volatility, partitioned using ARIMA model as the description in the data section.

In regressions of Model (5), the coefficients of the expected and unexpected volatility are both positive with statistical significance, indicating that the expected open interest rise with the both expected unexpected increased in volatility. This result is consistent with Chang et al. (2000), who study the S&P 500 index futures using similar model and report significant influence from both volatility components on open interest. The magnitude of effect from unexpected volatility, however, is smaller than those from the expected volatility. This suggests a less influential role of unexpected volatility than expected volatility to the open interest. This result differs from that of Chang et al. (2000), who report large coefficient for the unexpected than for the expected volatility. Since large volatility shock is almost always accompanied by substantial swing in price, hedgers may not instantaneously adjust hedge positions in response to volatility shock, during which hedging is extremely expensive. Instead, hedgers either wait for the end of the transient volatility shock or adjust positions according to the previous (expected) level of volatility. Because volatility tend to be clustering in time and can be forecasted with acceptable precision (Engle, 2004), the expected volatility provides important guidance to hedging strategies. This could be the reason why we observe stronger linkage between open interest and expected volatility but a lesser degree with unexpected volatility. Nevertheless, the effect of unexpected volatility in Model (5) remains significant holding constant the expected volatility, days to expiration, and weekly patterns.

9 It is somehow surprising to find that volatility is not significant linked the unexpected open interest. We speculate that, because volatility tends to cluster over time, hedgers can forecast volatility to certain extent and thus adjust their hedge positions ahead of the occurrence of volatility spikes. This would make the volatility more correlative to expected open interest than unexpected open interest. A detailed analysis in the timing of hedge may be warrant for future research.

The effect of either expected volatility or unexpected volatility on the unexpected open interest (*UOI*) is not confirmed. The coefficients for the unexpected volatility (ϕ_6) in the three regressions for Model (6) are not statistically significant. It is consistent with Model (4) that volatility is less correlated with unexpected open interest.

In sum, we find that the expected open interest is significant correlated with the predicted volatility and volatility shock, whereas the unexpected open interest is not. Results in general support Hypothesis 2, that open interest contains information about the latent hedging demand.

Table 4 Regressions of Open Interest on Spot Index Volatility

$$EOI_t = \alpha_3 + \beta_3\sigma_t + \gamma_3 TTM_t + \sum_{j=1}^{4}\kappa_{3,j}D_{t,j} + \varepsilon_t \tag{3}$$

$$UOI_t = \alpha_4 + \beta_4\sigma_t + \gamma_4 TTM_t + \sum_{j=1}^{4}\kappa_{4,j}D_{t,j} + \varepsilon_t \tag{4}$$

Volatility Proxies	Model (3)			Model (4)		
	$Parkinson_t$	GK_t	RS_t	$Parkinson_t$	GK_t	RS_t
Intercept (α)	50,170[a]	50,101[a]	50,247[a]	2,551[a]	2,582[a]	2,603[a]
	(49.77)	(49.67)	(49.96)	(10.95)	(11.07)	(11.20)
Volatility (β)	9.05[a]	11.71[a]	10.42[a]	-0.19	-0.64	-0.996
	(3.63)	(3.86)	(3.45)	(-0.33)	(-0.91)	(-1.43)
TTM_t (γ)	-119.61[a]	-121.42[a]	-121.65[b]	-84.23[a]	-84.15[a]	-84.07[a]
	(-3.45)	(-3.50)	(-3.51)	(-10.50)	(-10.49)	(-10.49)
Monday (κ_1)	-2,459b	-2,431[b]	-2,413[b]	-472.57[b]	-473.03[b]	-474.66[b]
	(-2.42)	(-2.39)	(-2.37)	(-2.01)	(-2.01)	(-2.02)
Tuesday (κ_2)	-691.29	-698.12	-704.15	-134.77	-133.88	-132.38
	(-0.69)	(-0.70)	(-0.70)	(-0.58)	(-0.58)	(-0.57)
Thursday (κ_3)	251.00	198.66	174.70	-3,087[a]	-3,083[a]	-3,076[a]
	(0.25)	(0.20)	(-0.70)	(-13.37)	(-13.35)	(-13.32)
Friday (κ_4)	-2,230[b]	-2,262[b]	-2,268[b]	-639.51[a]	-637.21[a]	-634.66[a]
	(-2.23)	(-2.26)	(-2.26)	(-2.76)	(-2.75)	(-2.74)
H_0: All $\kappa = 0$	3.03[b]	2.97[b]	2.92[b]	59.33[a]	59.16[a]	58.92[a]
Adj. R^2	0.0128	0.0136	0.0122	0.1395	0.1398	0.1402

Note: The OLS regression Model (3) and (4) examine the implications of Hypothesis 2 by regressing open interest on proxies of spot index volatility. EOI_t, and UOI_t are, respectively, the expected and unexpected component of open interest partitioned from OI_t using ARIMA model, where OI_t is the open interest of the two nearest expiration futures contracts. σ is the spot volatility proxy, which is measured by Parkinson (1980), Garman and Klass (1980) and Rogers and Satchell

(1991) on trading date *t*, respectively. All of the spot volatility proxies are multiplied by 10^6. TTM_t is the time-to-maturity (in days) of the highest open interest futures contracts. D_j (j = 1, 2, 3, 4) are the four daily dummies for the day-of-the-week effect. Numbers in parentheses for regression coefficients are t-values. The statistics of H_0 are the F-values. The superscript a, b and c indicate significance at the 1%, 5% and 10% confidence levels, respectively.

Table 5 Regressions of Open Interest on Expected and Unexpected Spot Volatility

$$EOI_t = \alpha_5 + \beta_5 \sigma_t^{expected} + \varphi_5 \sigma_t^{unexpected} + \gamma_5 TTM_t + \sum_{j=1}^{4} \kappa_{5,j} D_{t,j} + \varepsilon_t \quad (5)$$

$$UOI_t = \alpha_6 + \beta_6 \sigma_t^{expected} + \varphi_6 \sigma_t^{unexpected} + \gamma_6 TTM_t + \sum_{j=1}^{4} \kappa_{6,j} D_{t,j} + \varepsilon_t \quad (6)$$

Volatility Proxies	Model (5)			Model (6)		
	$Parkinson_t$	GK_t	RS_t	$Parkinson_t$	GK_t	RS_t
Intercept (α)	49,047[a]	49,083[a]	49,243[a]	2,735[a]	2,814[a]	2,778[a]
	(45.23)	(44.61)	(45.35)	(10.90)	(11.06)	(11.06)
Volatility						
Expected (β)	14.20[a]	17.59[a]	16.75[a]	-1.03	-1.98[b]	-2.10[b]
	(4.58)	(4.44)	(4.21)	(-1.44)	(-2.16)	(-2.28)
Unexpected (φ)	6.28[b]	9.06[a]	8.13[b]	0.26	-0.036	-0.60
	(2.35)	(2.79)	(2.58)	(0.42)	(-0.05)	(-0.82)
TTM_t (γ)	-121.17[a]	-123.32[a]	-123.98[b]	-83.97[a]	-83.71[a]	-83.66[a]
	(-3.50)	(-3.56)	(-3.58)	(-10.48)	(-10.45)	(-10.44)
Monday (κ_1)	-2,461[a]	-2,506[b]	-2,523[b]	-472.18[c]	-456.14[c]	-455.53[c]
	(-2.43)	(-2.47)	(-2.48)	(-2.01)	(-1.94)	(-1.94)
Tuesday (κ_2)	-669.43	-761.11	-781.73	-138.34	-119.52	-118.86
	(-0.67)	(-0.76)	(-0.78)	(-0.60)	(-0.52)	(-0.51)
Thursday (κ_3)	299.80[a]	185.26	158.04	-3,095[a]	-3,080[a]	-3,073[a]
	(0.30)	(0.19)	(0.16)	(-13.41)	(-13.35)	(-13.32)
Friday (κ_4)	-2,216[b]	-2,251[b]	-2,274[b]	-641.85[a]	-639.76[a]	-633.64[a]
	(-2.21)	(-2.25)	(-2.27)	(-2.77)	(-2.76)	(-2.74)
H_0: $\beta_i = \phi_i$	7.74[a]	5.31[b]	5.94[b]	3.86[b]	5.16[b]	3.38[c]
H_0: All κ = 0	3.10[b]	3.03[b]	3.03[b]	59.66[a]	59.44[a]	59.17[a]
Adj. R^2	0.0159	0.0155	0.0145	0.1406	0.1414	0.1412

Note: Regressions (5) and (6) are used to examine the implications of Hypothesis 2. The dependent variables are EOI_t and UOI_t are, respectively, the expected and unexpected component of open interest partitioned from OI_t using ARIMA model, where OI_t is the two nearest expiration futures contracts. $\sigma_t^{expected}$ and $\sigma_t^{unexxpected}$ are, respectively, the expected and unexpected component of spot volatility proxy, which is measured by Parkinson (1980), Garman and Klass (1980) and Rogers and Satchell (1991) in different regressions. All of the spot volatility proxies are multiplied by 10^6, and each spot volatility proxy is partitioned into the expected and unexpected volatilities using ARIMA model. TTM_t is the time-to-maturity (in days) of the highest open interest futures contracts. D_j (j = 1, 2, 3, 4) are the four daily dummies for the day-of-the-week effect. Numbers in parentheses for regression coefficients are t-values. The statistics of H_0 are the F-values. The superscript a, b and c indicate significance at the 1%, 5% and 10% confidence levels, respectively.

4.4 Test Results of Open Interest Representing Divergence in Opinions

Table 6 presents the results for the test of implications (5) to (6) in Hypothesis 3, which relates the open interest to the divergence of opinions. In Models (7) and (8), the dependent variables are respectively volume and the absolute value of the difference between the bid and ask depth. The key independent variables are the signed open interest changes, $DiOI_1|\Delta OI|$ for OI increment and $DiOI_2|\Delta OI|$ for OI decrement. The control variables are expected open interest, unexpected open interest, market depth (for Model (7) only), total volume (for Model (8) only), time to expiration (TTM), and dummies for the day-of-the-week effect (D_j). The regression results are summarized as follows.

Consistent with the prediction of implication (5), increments and decrements in open interest have different impacts on the change in volume. In Model (7), one unit increment in open interest raises volume by 5.9722 units. The impact is greater than the effect (3.4629 units) of one unit decrement in open interest on volume. The difference is statistically significant according to the F-test for null hypothesis of $\beta_1 = \beta_2$ with an F-value of 54.42. Our results suggest that the effect of open interest increases on trading volume is greater than the effect of open interest decreases on trading volume. It indicates that increments of open interest may reflect a greater degree of divergence in investors' opinions, supporting the view of Bessembinder et al. (1996). The positive relation between increments in open interest and volume also is consistent with practitioners' view that divergences in traders' opinions will cause volume to rise.

Model (8) examines the information contents of open interest with regard to the symmetricity in bid and ask depths, using the absolute difference of bid-side and ask-side depths ($|BDEP - ADEP|$) as a proxy for divergence in opinion. The larger the $|BDEP - ADEP|$ is, the more convergence the opinions are. Our regression results show a negative β_{81}. Although the coefficient is statistically insignificant, the sign is consistent with the conjecture that open interest increment is associated with more symmetric depths on buy- and sell-side of the order book. The significantly positive β_{82} indicates that open interest decrement is accompanied by a larger depth deviation between the buy- and sell-side of the order book. Results are in general consistent with implication (6), thus support the hypothesis that open interest can reflect the divergence in traders' opinions.

In sum, we find that trading volume is affected asymmetrically by the upward and downward movement in open interest. The result supports the hypothesis that changes in open interest proxy for changes in the divergence of opinion across traders. Moreover, open interest increment (decrement) is associated with smaller (larger) depth imbalance between buy-side and sell-side of the limit order book. It indicates that the divergence in opinion, proxied by a small depth imbalance, is associated with greater open interest. Result again is consistent with the hypothesis that open interest has information content about the divergence/convergence in traders' opinions.

Table 6 Regressions of Proxies for Divergence in Opinion on Signed Open Interest Changes

$$VOL_t = \alpha_7 + \sum_{i=1}^{2} \beta_{7i}\ DiOI_i \left|\Delta OI_t\right| + \theta_7 EOI_t + \eta_7 UOI_t + \varphi_7 DEP_t + \gamma_7 TTM_t + \sum_{j=1}^{4} \kappa_{7j} D_j + \varepsilon_t \quad (7)$$

$$\left|BDEP_t - ADEP_t\right| = \alpha_8 + \sum_{i=1}^{2} \beta_{8i} DiOI_i \left|\Delta OI_t\right| + \theta_8 EOI_t + \eta_8 UOI_t + \varphi_8 VOL_t + \gamma_8 TTM_t + \sum_{j=1}^{4} \kappa_{8j} D_j + \varepsilon_t \quad (8)$$

	Model (7)	Model (8)
	VOL_t	$\vert BDEP_t - ADEP_t\vert$
Intercept (α)	-10,146[a]	24.46[a]
	(-3.26)	(10.57)
Open interest		
Increment (β_1)	5.9722[a]	-0.0006
	(7.86)	(-0.98)
Decrement (β_2)	-3.4629[a]	0.0012[b]
	(-5.74)	(2.38)
EOI_t (θ)	1.7742[a]	-0.00005
	(44.38)	(-1.12)
UOI_t (η)	-3.2117[a]	0.0014[b]
	(-5.12)	(2.51)
DEP_t (φ_7)	-54.8340[a]	
	(-13.50)	
VOL_t (φ_8)		-0.0002[a]
		(-10.00)
TTM_t (γ)	301.23[a]	0.2293[a]
	(4.78)	(4.27)
Monday (κ_1)	-3,635[b]	1.6656
	(-2.05)	(1.10)
Tuesday (κ_2)	-1,265	2.2960
	(-0.73)	(1.55)

	Model (7)	Model (8)
	VOL_t	$\|BDEP_t - ADEP_t\|$
Thursday (κ_3)	350 (0.19)	3.7111[b] (2.39)
Friday (κ_4)	1,270 (0.73)	3.4306[b] (2.30)
H_0: $\beta_1 = \beta_2$	54.42[a]	2.89[c]
H_0: all $\kappa = 0$	2.23[b]	1.94
Adj. R^2	0.5696	0.1084

Note: Regressions (7) and (8) test the implications of Hypothesis 3. The dependent variables are volume (VOL_t), and the absolute difference between bid and asked depths ($|BDEP_t - ADEP_t|$), respectively. $|\Delta OI_t|$ is the unsigned change in open interest. $DiOI_i$ (I = 1, 2) are dummy variables representing the increment or decrement of open interest. $DiOI_1$ = 1 when $\Delta OI > 0$, and zero otherwise; $DiOI_2$ = 1 when $\Delta OI < 0$, and zero otherwise. EOI_t, (expected open interest) and UOI_t (unexpected open interest) are partitioned from OI_t using ARIMA model. TTM_t is the time-to-maturity (in days) of the highest open interest futures contracts. D_j (j = 1, 2, 3, 4) are the four daily dummies for the day-of-the-week effect. Numbers in parentheses for regression coefficients are t-values. H_0: $\beta_1 = \beta_2$ is the joint test (F-statistics) for whether the effects of increments and decrements in open interest are the same. The significance of the day-of-the-week effect is jointly tested by H_0: all $\kappa = 0$, also reporting the F-statistics. The superscript a, b and c indicate significance at the 1%, 5% and 10% confidence levels, respectively.

4.5 Robustness Analysis

Note that the process detailed in section 3.1 for decomposing the OI is critical to this study. Because the empirical results are based on the decomposition of open interest, the model for decomposition should be chosen with caution. In this section, we explain the reasons of our preference for a more precise model over other parsimonious models, and discuss the robustness of our main findings using alternative decomposition models. Table 7 presents seven alternative ARIMA models and their time series properties, along with the final model (Model (8) with bold text) used in the study for the OI decomposition. The final model has a few advantages over its parsimonious alternatives. First, the residuals from our ARIMA model are nearly white noise series. There is no serial correlation up to 60 lags. Second, outliers should be controlled in the univariate model. Third, the model has very small AIC and SBC among other more parsimonious specifications. For the three models (Model (5), (6) and (7) in italic) with even smaller AIC and SBC, the residuals are not white noise according to the Q-statistics. Models with relatively parsimonious form (e.g., Model (1) to (4)) clearly is not econometrically appealing, if judged by the AIC and SBC.

Two disadvantages associated with a more complicated model are the loss of degree-of-freedom and the difficulty in interpretation. The loss of degree-of-freedom should not pose much threat to our results because we have large sample size (2,226 observations) relatively to the number of parameters (10 parameters, p = 1, 3, 19, 20, 21 and q = 3, 24, 26, 39, 44) to be estimated. In our case, interpretation of the decomposed series is unimportant because the purpose of model is to separate the expected and unexpected components of *OI* series. The model describes the "expected" *OI* series, whose time series property has never been discussed in any existing theory or paper. As a result, interpreting the contents and properties of the decomposed series is less in need for this case (see similar argument in Bessembinder and Seguin (1993)).

It appears that the advantages of the more precise model outweigh its disadvantages. For these reasons, we favor the more precise model over the parsimonious ones.

To be concrete, we test the robustness of our main findings using alternative models with more parsimonious form. We use ARIMA Models (1) to (4) in Table 7 as alternative models for the decomposition of *OI*. We then used the decomposed series from each alternative model to perform regressions Model (2), (3), and (4) in Table 3 and 4. The results of the final model are unaltered except in few occasions.[10] The tests indicate that the empirical results presented in the manuscript are robust to different models of OI decomposition.

Table 7 Alternative ARIMA Models for Robustness Analysis

Model	p (AR terms)	q (MA terms)	AIC	SBC	ACF & PACF	Q-statistics
Alternative Models						
1	1,2	1	19.37242	19.38012	20,24,44	20(0.000)
2	1,2,3,4,5,6	1,2,3	19.37088	19.39401	20,24,44	20(0.000)
3	1~19	1,2,3	19.34881	19.40563	23,44	44(0.000)
4	1,2,3,19	1,2,3	19.34635	19.36185	20,44	20(0.000)
5	*1,3,19,20,21*	*3,20,24,26,39,44*	*19.30113*	*19.32956*	*40*	*12(0.085)* *13(0.083)* *60(0.073)*
6	*1,3,19,20,21*	*20,24,26,39,44*	*19.30276*	*19.32860*	-	*11,12…* *(>0.020)*
7	*1,3,20,21*	*3,20,24,26,39,44*	*19.30231*	*19.32815*	-	*56(0.074)* *60(0.03)*
Final Model						
8	**1,3,19,20,21**	**3,24,26,39,44**	**19.31195**	**19.33779**	**-**	**-**

10 Results for this robustness test are not reported for the purpose of brevity. A summary table of the findings using alternative decomposition models is available upon request.

Note: The *p* and *q* respectively stand for the AR and MA terms of the ARIMA (*p*, 0, *q*) model. The AIC and SBC are information criterions proposed by Akaike (1974) and Schwarz (1978) respectively. The residual diagnostics report the ACF, PACF and the Ljung-Box Q-statistics. We show that the k lags of ACF and PACF of residual which are not within these bounds and it is significantly different from zero at the 5% significance level approximately. The column of Q-statistics provides the lag number of the Q-statistics and their corresponding p-value in the parenthesis. The last model (Model (8) in bold text) is the one used in the study for the OI decomposition. This model has small value of AIC and SBC and no serial correlation up to 60 lags. For the three models (Model (5), (6) and (7) in italic) with even smaller AIC and SBC, the residuals are not white noise according to the Q-statistics.

5. Conclusions

The study provides interpretation to the information contents of open interest, a variable serving for many proxies in literature. We analyze the index futures traded in Taiwan to test three hypotheses regarding the information contents of open interest. Specifically, we test whether open interest reflects market participation, hedging demand and divergence in traders' opinions.

The results show that increase in open interest is accompanied by higher trading volume, greater depth provision, and lower market impact costs. The results are consistent with Bessembinder and Seguin (1993) that participation, proxied by open interest, enhances market liquidity. In addition, both expected and unexpected open interest are positively related to liquidity proxies, supporting the findings of Martell and Wolf (1987), Moser (1994) and Bessembinder and Seguin (1993). Our findings of the close linkage between open interest and liquidity variables support the hypothesis that open interest reflects the degree of market participation.

Our empirical results also corroborate with the hypothesis that open interest representing demand for hedging. Regression results show significantly positive relationships between open interest and three spot volatility proxies. The expected component of open interest moves directly with index volatility, indicating that greater spot market volatility motivates hedging demand, which adds open interest on futures markets. The evidence conforms to the viewpoints of Chen et al. (1995), Chang et al. (2000) and Aguenaou et al. (2011), who assert that open interest reflects hedging demand.

Our results agree with the hypothesis that open interest represents the divergence of traders' opinions. We find that both increments and decrements in open interest have significant but asymmetric impacts on the change in volume. The effect of open interest increases on trading volume is greater than the effect of open interest decreases on trading volume, consistent with the implications suggested in Bessembinder et al. (1996). Using the absolute difference of bid-side and ask-side depths as a proxy for divergence in opinions, we find that open interest increment is associated with more symmetric depths on two sides of the order book, whereas open interest decrement is accompanied by a larger discrepancy between the buy- and sell-side of the order book. Evidence shows that a large open interest signifies the more divergence in traders' outlook.

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Appendix A

We estimate the Box-Jenkins ARIMA model suggested by Bessembinder and Seguin (1993) to partition open interest into expected and unexpected components. The three phases of the ARIMA (*p,d,q*) are identification, estimation and diagnosis, in that order. First, if the data explodes over time, it needs to be differenced *d* times to achieve stationary value by the unit root tests. In our result, the OI variable is a stationary *I(0)* time series. We then utilize the correlogram including the autocorrelation function (ACF) and the partial autocorrelation function (PACF) to decide the order (*p* and *q*) of the autoregressive, or AR, term and the moving average, or MA, term. Second, we estimate the candidate ARIMA specification to obtain the all parameters of the ARIMA model. The non-significant intercept and coefficients are omitted for a parsimonious principle and then repeat the second step again. Third, we make sure that there is no serial correlation in the residuals, using the Ljung-Box Q statistics test for diagnostic checks. The null hypothesis is that there is no serial correlation in the residuals up to the specified order. If the result rejects the null hypothesis, we should return to the first and second steps. We also use AIC (Akaike, 1974), SBC (Schwarz, 1978) and extended ACF (Tsay and Tiao, 1984) to verify the chosen number of lags. Following the above steps, the lowest AIC and SBC values are 19.31195 and 19.33779 respectively. The final model used to decompose the OI series is ARIMA [(1,3,19,20,21), 0, (3,24,26,39,44)] with parameters as follows:

$$OI_t = \underset{(57.55)}{0.903OI_{t\text{-}1}} + \underset{(2.76)}{0.045OI_{t-3}} + \underset{(2.24)}{0.049OI_{t-19}} + \underset{(6.02)}{0.173OI_{t-20}} - \underset{(-7.95)}{0.170OI_{t-21}}$$

$$+\varepsilon_t - \underset{(-2.07)}{0.047\varepsilon_{t-3}} + \underset{(4.04)}{0.087\varepsilon_{t-24}} - \underset{(-2.34)}{0.05\varepsilon_{t-26}} - \underset{(-3.27)}{0.071\varepsilon_{t-39}} + \underset{(6.32)}{0.136\varepsilon_{t-44}}$$

Numbers in parentheses are t-statistics. All coefficients are significant at the 5% level. The ACF and PACF of residuals at least 60 lags are nearly zero and their Ljung-Box Q statistic test with large p-values, suggesting that the null hypothesis of no autocorrelation in the residual series is not rejected at a 5% significant level. The results of extended ACF are similar to the above results.

Appendix B

The three volatility proxies are identified by ARIMA models with the following parameter estimates:

$$\begin{aligned}
Parkinson_t = {} & \underset{(5.39)}{87.25} + \underset{(13.73)}{0.85}Parkinson_{t\text{-}1} + \underset{(2.22)}{0.14}Parkinson_{t\text{-}4} - \underset{(-2.51)}{0.06}Parkinson_{t\text{-}9} \\
& + \underset{(1.87)}{0.04}Parkinson_{t\text{-}10} + \varepsilon_t - \underset{(-9.54)}{0.67}\varepsilon_{t-1} - \underset{(-3.49)}{0.19}\varepsilon_{t-4} + \underset{(6.20)}{0.13}\varepsilon_{t-25} - \underset{(-0.46)}{0.09}\varepsilon_{t-26}
\end{aligned}$$

$$\begin{aligned}
GK_t = {} & \underset{(6.71)}{77.5} + \underset{(20.29)}{0.80}GK_{t\text{-}2} + \underset{(3.27)}{0.07}GK_{t\text{-}7} + \underset{(2.76)}{0.06}GK_{t\text{-}15} + \varepsilon_t + \underset{(11.37)}{0.2}\varepsilon_{t-1} - \underset{(-15.27)}{0.69}\varepsilon_{t-2} \\
& - \underset{(-2.85)}{0.06}\varepsilon_{t-5} - \underset{(-3.84)}{0.07}\varepsilon_{t-17} + \underset{(6.05)}{0.13}\varepsilon_{t-25} - \underset{(-3.72)}{0.08}\varepsilon_{t-27} + \underset{(3.54)}{0.06}\varepsilon_{t-33}
\end{aligned}$$

$$\begin{aligned}
RS_t = {} & \underset{(4.55)}{71.93} + \underset{(9.13)}{0.15}RS_{t\text{-}1} + \underset{(24.53)}{0.8}RS_{t\text{-}12} + \underset{(1.70)}{0.03}RS_{t\text{-}15} + \varepsilon_t \\
& - \underset{(-21.98)}{0.77}\varepsilon_{t-2} - \underset{(-3.87)}{0.07}\varepsilon_{t-17} + \underset{(1.93)}{0.03}\varepsilon_{t-25} - \underset{(-2.27)}{0.03}\varepsilon_{t-32}
\end{aligned}$$

Numbers in parentheses are t-statistics. All coefficients are significant at the 5% level. None of the Ljung-Box Q-statistics for lag lengths 1-60 are significant at the 5% level.

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