國立交通大學

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碩 士 論 文

買賣權隱含波動度差與現貨報酬動能：ETF 選擇權與 ETF 市場分析

An analysis of Implied Volatility Spread and Underlying Asset Momentum across ETF Option and ETF market

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摘 要

本研究主要在探討ETF選擇權價格與ETF現貨報酬動能之間的動態關係，採用美國S&P 500指數、Nasdaq 100指數及DJIA指數的ETF與ETF選擇權商品來研究，觀察資訊傳遞在不同的指數類型中有何差異。利用時間序列模型檢驗ETF選擇權隱含波動度差與ETF過去報酬期間的相關性，以觀察在ETF選擇權市場中是否存在動能交易的現象，藉此了解ETF選擇權交易者除了對於未來趨勢的捕捉之外，是否會參考過去ETF現貨市場的績效。另外比較ETF化與非ETF化的指數選擇權商品，對於動能交易的影響性，以了解指數的可交易性是否為研究選擇權與現貨市場相關議題時，必須控制的重要因素。

關鍵詞

動能、選擇權、隱含波動度差、指數股票型基金

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ABSTRACT

The purpose of this study is to investigate the dynamic relationship between ETF options' prices and the ETF market momentum. Using the ETF and the ETF option collected from U.S. S&P 500 Index, Nasdaq 100 Index, and DJIA Index, we observe the difference on information transmission among different types of Indices. To examine our thesis, we employ the time-series model to investigate the relation between the implied volatility spreads of ETF options and the returns on ETF during a period. In other words, we observe whether there exists momentum trading in ETF option market and attempt to recognize that whether the traders of ETF options not only chase the market trend but also refer to the ETF performance in the past. Finally we compare the impacts on momentum trading between ETF option and index option to realize that whether the trading practicability of index is the essential factor to control when investigating the related subjects of option market and spot market.

Keywords

Momentum、Option、Implied volatility spread、Exchange traded funds

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1. Introduction

Exchange Traded Funds, or ETFs, are an investment vehicle traded on stock exchanges, much like stocks or bonds. ETFs are index-based investment products that allow investors to buy or sell shares of entire portfolios of stock in a single security. Moreover, an ETF is a type of investment company whose investment objective is to achieve the same return as a particular market, and is similar to an index fund in that it will primarily invest in the securities of companies that are included in a selected market index, such as the Dow Jones Industrial Average or the S&P 500.

ETFs had their genesis in 1989 with Index Participation Shares, an S&P 500 proxy that traded on the American Stock Exchange and the Philadelphia Stock Exchange. This product, however, was short-lived after a lawsuit by the Chicago Mercantile Exchange was successful in stopping sales in the United States. similar product, Toronto Index Participation Shares, started trading on the Toronto Stock Exchange in 1990. The shares, which tracked the TSE 35 and later the TSE 100 stocks, proved to be popular. The popularity of these products led the American Stock Exchange to try to develop something that would satisfy SEC regulation in the United States.

Standard & Poor's Depository Receipts (SPY) are shares of a family of exchange-traded funds (ETFs) traded in the United States and managed by State Street Global Advisors (SSgA). Informally, they are also known as Spyders or Spiders. The name is an acronym for the first member of the family, the Standard & Poor's Depository Receipts (SPY), the biggest ETF in the U.S., which is designed to track the S&P 500 stock market index. SPDRs were launched by Boston fund manager SSgA in 1992–1993 as the first exchange-traded fund shares still traded in the United States (preceded by the short-lived Index Participation Shares that launched in 1989.) Devised by American Stock Exchange executive Nathan Most, the fund first traded on that market, but has since been listed elsewhere, including the New York Stock Exchange (NYSE).

The Dow Jones Industrial Average (DJIA) is the most widely quoted stock index. World wide media reports constantly quote DJIA updates. It may be the easiest stock index to track, but the entire index was not easy to trade until the Chicago Board of Trade (CBOT) introduced the DJIA futures contracts in October 1997. Then, it have seen the emergence of the exchange-traded fund (ETF), DIAMOND, in January 1998

The NASDAQ-100 Trust Series 1 Exchange-traded fund, sponsored and overseen since March 21, 2007 by Powershares, trades under the ticker NASDAQ: QQQQ. On December 1, 2004, it was moved from the American Stock Exchange where it had the symbol QQQ to the NASDAQ and given the new four letter code QQQQ. It is sometimes referred to as the "Quad Qs," "Cubes," or simply as "the Qs." In 2000 it was the most actively traded security in the United States, but has since dropped to second place after Standard & Poor's Depositary Receipts. On July 17, 2007, the ETF closed above $50 for the first time since early 2001.

2003 year is a turning point for ETF development occurred the mutual fund scandal which was the result of the discovery of illegal late trading and market timing practices on the part of certain hedge fund and mutual fund companies. In U.S, the number of mutual fund investors has approached half the families so that this market is corresponsively mature. However, these illegal trading behaviors got plastered the investor’s confidence deeply.

ETFs generally provide the easy diversification, Buying and selling flexibility, Transparency, low expense ratios, and tax efficiency of index funds, while still maintaining all the features of ordinary stock, such as limit orders, short selling, and options. Because ETFs can be economically acquired, held, and disposed of, some investors invest in ETF shares as a long-term investment for asset allocation purposes, while other investors trade ETF shares frequently to implement market timing investment strategies. ETFs generally have lower costs than other investment products because most ETFs are not actively managed and because ETFs are insulated from the costs of having to buy and sell securities to accommodate shareholder purchases and redemptions. ETFs typically have lower marketing, distribution and accounting expenses, and most ETFs do not have. ETFs can be bought and sold at current market prices at any time during the trading day, unlike mutual funds and unit investment trusts, which can only be traded at the end of the trading day. As publicly traded securities, their shares can be purchased on margin and sold short, enabling the use of hedging strategies, and traded using stop orders and limit orders, which allow investors to specify the price points at which they are willing to trade. ETFs generally generate relatively low capital gains, because they typically have low turnover of their portfolio securities. While this is an advantage they share with other index funds, their tax efficiency is further enhanced because they do not have to sell securities to meet investor redemptions. ETFs provide an economical way to rebalance portfolio allocations and to "equitize" cash by investing it quickly. An index ETF inherently provides diversification across an entire index. ETFs offer exposure to a diverse variety of markets, including broad-based indexes, broad-based international and country-specific indexes, industry sector-specific indexes, bond indexes, and commodities. ETFs, whether index funds or actively managed, have transparent portfolios and are priced at frequent intervals throughout the trading day.

Although there are many advantages to invest ETFs, it still go along with some risks. When the Portfolio invests in Underlying ETFs, it will indirectly bear its proportionate share of any fees and expenses payable directly by the Underlying ETF. Therefore, the Portfolio will incur higher expenses, many of which may be duplicative. In addition, Underlying ETFs are also subject to the following risks: (i) the market price of an Underlying ETF’s shares may trade above or below its net asset value; (ii) an active trading market for an Underlying ETF’s shares may not develop or be maintained; (iii) the Underlying ETF may employ an investment strategy that utilizes high leverage ratios; (iv) trading of an Underlying ETF's shares may be halted if the listing exchange's officials deem such action appropriate, the shares are delisted from the exchange, or the activation of market wide "circuit breakers" (which are tied to large decreases in stock prices) halts stock trading generally; or (v) the Underlying ETF may fail to achieve close correlation with the index that it tracks due to a variety of factors, such as rounding of prices and changes to the index and/or regulatory policies, resulting in the deviating of the Underlying ETF's returns from that of the index. Some Underlying ETFs may be thinly traded, and the costs associated with respect to purchasing and selling the Underlying ETFs (including the bid-ask spread) will be borne by the Portfolio.

According to capital markets are more free and international, the derivatives which provided low trading cost and high leverage rapidly develop. Especially in options and implied option investment which become the indispensable financial implements, so there are more and more investors to put money into option markets. The option trading includes abounding market information and psychology, thus the issue that the dynamic relationship between option market and spot market is become important. Because of the option market development, ETFs are also listed ETF option, such as SPY option, QQQQ option, and the DIA option. Combining long-term ETF momentum with option price, this study is desirous that whether the ETF returns influence the option price. It implies that people invest the ETF options which are less familiar whether they would care about past performance as mutual funds. In other words, whether inform traders anticipate that the behavior of momentum investors alter their trading behavior to profit from the follower's expected reaction. Therefore, informed traders buy more the fundamental value ETF and reinforce the trading by positive feedback traders and drive the price above its fundamental option value.

To make a comprehensive survey of previous literatures, there are three particular researching contributions in our study. First, although many literatures discuss the issue between ETF and index market or between ETF and index futures market, there is no study investigating between ETF and ETF option market. Option is one of the most important financial implements over the world, therefore investigating between ETF and ETF market is another important issue.

Second, past literatures regularly used index data to discuss the dynamic relationship between spot market and option market. It does not conform to realistic situation for arbitrage or trading index because trading the components of index has much cost and seriously asynchronous trading. Hence, Using index data has doubts for arbitrage theory and relative Price Discovery issues. ETF is the best investment to trading index instead of index data. Also, in our thesis, we adopted SPY and S&P 500 (DIA and DJIA) data to examine the cross momentum trading and to figure out whether the discrepancy caused by tradable character (ETF and non-ETF).

Third, this study place emphasis on long-term relationship between ETF and ETF option market. We adopt implied volatility spread and past ETF returns to examine the dynamic relation. We would like to chase the more precise trading behavior and figure out how the trading strategy differs from spot market and option market.

The rest of the paper is organized as follows. In section II, we present the related literature. In section III, we describe our methodology which was used to examine the relationship between implied volatility spread and past underlying asset returns. The data selection is also introduced in Section III. Section IV reports the empirical results and robustness test and Section V concludes the paper.

2. Literature Review

2.1 Option Market and Stock Market

In discussing the relationship between option market and sock market, the most studies focus on the issue of the Price Discovery. The Price Discovery, meaning when the market accepts new information, investors will make a judgement based on it and trade in financial market by that, then asset would adjust rapidly to its equilibrium price by market mechanism. Namely, from formulation of diffusion of information to investors' interpretation and trading, the course which assets price reach equilibrium in succession can be called the Price Discovery. The Price Discovery is a characteristic of efficient market that causes market price to contain all information sufficiently and immediately. Thus, it accounts for Dominant market and Price lead-lag relationship.

In the Perfect Market, perfect substitute attribute make asset has only one price because when price discrepancies come about, the arbitrage opportunity is appeared at once. In other words, under the arbitrage action, there is no lead-lag relationship between stock and option market. In fact, there are several kinds of trading cost in real market and dissimilar market microstructures in different asset markets. Therefore, information transmission is inconsistency making variance of price movement. Besides, in the imperfect market, information might be exposed by trading actions, so any news is implied in a dominant market foremost.

Past evidence on the lead-lag relation between option and stock prices has been almost US based. It is however often conflicting. Early literatures found that stock options lead the underlying stocks. Manaster and Rendleman (1982) adopted 172 stocks with listed options and 805 trading days. They examine close-to-close returns of portfolios based on the relative difference between stock and option prices and find that closing option prices contain information that is not contained in closing stock prices. However, a serious problem results from the use of closing data, since the Chicago Board Options Exchange (CBOE) closes ten minutes after the close of the stock market. It is possible that the additional information contained in closing option prices merely reflects more recent rather than better information.

Bhattacharya (1987) in order to overcome the three major limitations of MR, namely, (a) daily closing stock and option prices, (b) their non-simultaneity, and (c) the non-consideration of bid/ask spreads for stocks and options, he used the raw data which contains a record for each transaction and another for each bid/ask update for every option series. He compares implied bid/ask stock prices (calculated from call option prices) to actual bid/ask stock prices to calculate arbitrage opportunities. The stock is considered underpriced (overpriced) if the implied bid (ask) is higher (lower) than the actual ask (bid). A simulated trading strategy based on these arbitrage signals indicates that profits are insufficient to cover transaction costs for all intraday holding periods. However, the Manaster and Rendleman (1982) results are confirmed by Bhattacharya's finding of statistically significant excess returns for overnight holding periods. Bhattacharya's test design however suffers in that it only detects whether the option market leads the stock market and not vice versa. Although Bhattacharya recognises this as a problem, the reverse simulations are not performed and although he knows the problem, he didn't resolve all doubts.

Anthony (1988) required two data-selecting criterions. One is that the call option and their underlying common shares are listed contemporaneously for period from January 1, 1982 through June 30, 1983, and the other is that sample firms must be listed on either the New York Stock Exchange (NYSE) or the American Stock Exchange (AMEX). He uses daily data to examine whether trading in one market causes trading in the other. His analysis is based on econometric tests for causality derived from the work of Granger (1969). Anthony concludes that trading in call options leads underlying assets by one day. However, he finds this to be the case for only thirteen firms, whereas stock volume leads option volume for four firms and no unambiguous direction exists for eight firms. Anthony's results are subject to the same caveats as Manaster and Rendleman due to the non-simultaneity of the closing times for the two markets.

Stephan and Whaley (1990) conceived that the approach must circumvent two major problems of the previous studies. First, transaction-by-transaction data from the stock and option markets are used. Thus, the biases inherent in the non-simultaneity of closing prices in the two markets are avoided. Second, the analysis focuses directly on the lead/lag relation between the intraday price changes in the stock and option markets rather than indirectly through simulating a trading strategy. They examine empirically the intraday price change transformed into implied stock price changes over five-minute intervals and trading volume relations between stocks and options for a sample of firms whose options were actively traded on the CBOE during the first quarter of 1986. They use multi-variable time series regression analysis to estimate the lead/lag relation between the price changes and trading volume in the option and stock markets. Inconsistent with earlier studies, they find that trading in the stock market leads the option market about fifteen to twenty minutes on average both in terms of price changes and trading activity.

Chan, Chung and Johnson (1993) first confirm Stephan and Whaley's results using data for the same period of analysis and then show their results can be explained as spurious leads induced by infrequent trading of options. Specifically, they show that the stock price lead disappears when the average of the bid and ask prices is used instead of transaction prices. They also show that minimum price variation rules contribute to the documented stock lead because they cause greater discreteness for the trading of options, since stock and option price movements have a non-linear relationship.

Chan, Chung, and Fong (2002) argued that although Stephan and Whaley (1990) investigate both price changes and volume in the two markets, they analyze the price change relationship and the volume relationship separately. Thus, they provides a comprehensive analysis of the interdependence of net trade volume (buyer-initiated trading volume minus seller-initiated trading volume) and quote revisions for actively traded NYSE stocks and their CBOE-traded options. They show that stock net trade volume, but not option net trade volume, predicts contemporaneous and subsequent stock and option quote revisions, suggesting that informed investors initiate trades in the stock market only. On the other hand, option quote revisions, as well as stock quote revisions, predict subsequent quote revisions in the other market.

2.2 Price Discovery of ETF

Because ETF is become more popular since A.D. 1997 , there are not abundant literature on Price Discovery of ETF. Chu, Hsieh and Tse (1999) show in a Vector Error Correction framework that price discovery still takes place on S&P 500 futures. SPDRs only make a small contribution to the common factor, but more than the spot market. Since the study is based on the ETFs' first year of trading, it is necessary to view these results with some caution. SPDRs only began to exhibit a high-trading volume years later.

Over the March-May 2000 period, Hasbrouck (2003) analyzes the price discovery process using the information share approach of Hasbrouck (1995) for three major U.S. indices. Investors can take positions on the S&P 500 and Nasdaq-100 indices through individual stocks, floor-traded futures contracts, electronically-traded E-mini futures contracts, options or ETFs. The largest informational contributions come from the futures market, with the ETF market playing a minor, though significant role. Interestingly enough, there was no E-mini contract for the S&P MidCap 400 over the sample period and the ETF information share is the most important for this last index.

Recent work by Tse, Bandyopadhyay and Shen (2006) shows that although the E-mini DJIA futures contracts dominate price discovery, Diamonds also play a very significant part in the process. Their results for the S&P 500 highlight a contribution of about 49% for the ETF. However, this does not doubt on Hasbrouck's (2003) results since they are based on floor-based quotes and trades from the AMEX whereas Tse, Bandyopadhyay and Shen use quotes from the ArcaEx Electronic Crossing Network. The anonymous and immediate trading execution obtained on electronic trading platforms may indeed attract informed trading.

2.3 Option Prices and Stock Market Momentum

According to previous literature, we realize the long-term lead-lag relationships in the options and the underlying asset markets have less been investigated compared to the study of Price discovery in short-term. In imperfect markets, option price can be affected by the momentum of the underlying asset through a number of channels (Amin, 2003), such as investors' expectations about future stock returns, their demand for portfolio insurance, or their attitude toward the higher moments of stock distribution. First, investors' expectations about future stock return can depend on past stock return. Namely, it means that price movements in the underlying asset market cause price pressures in the options market at a later market, which suggests that a rise in the asset price triggers trading in the options market. This kind of trading behavior is known as momentum trading and is described in the literature extensively by several authors. Delong, Shleifer, Summers, and Waldmann (1990) introduce positive feedback (momentum) traders, who buy when prices rise and sell when prices fall and who may have a variety of incentives for this behavior. These incentives include trend chasing, inability to meet margin call, or portfolio insurance. Inform traders anticipating the behavior of momentum investors alter their trading behavior to profit from the follower's expected reaction. Therefore, informed traders buy more than what the fundamental value would suggest which reinforces the trading by positive feedback traders and drives the price above its fundamental value. Lo and Mackinlay (1988) show that the cross-sectional interaction of security returns over time is an important aspect of stock price dynamics. As an example, we document the fact that stock returns are often positively cross-autocorrelation, which reconciles the negative serial dependence in individual security returns with the positive auto correlation in market indexes. Jegadeesh and Timan (1993) constructed trading strategies which buy past winners and sell past losers realize significant abnormal returns over the 1965 to 1989. For example, the strategy they examine in most detail, which select stock based on their past 6-month returns and holds them for 6 months, realizes a compounded excess return of 12.01% per year on average. The returns of the zero-cost winners minus losers portfolio were examined in each of the 36 months following the portfolio formation date. With the exception of the first month, of the first month, this portfolio realizes positive returns in each of the 12 months after the formation date. However, the longer-term performances of these past winners and losers reveal that half of their excess returns in the year following the portfolio formation date dissipate within the following 2 years.

Chan, K. C.'s (1998) contrarian stock selection strategy consists of buying stocks that have been losers and selling short stocks that have been winners. Preached by market practitioners for years, it is still in vogue on Wall Street and La Salle Street. The strategy is formulated on the premise that the stock market overreacts to news, so winners tend to be overvalued and losers undervalued; an investor who exploits this inefficiency gains when stock prices revert to fundamental values. Many investment strategies, such as those based on the price/earnings ratio, or the book/market ratio, can be regarded as variants of this strategy.

Conrad, Kaul, and Nimalendran (1998) also constructed trading strategies buying past winners and selling past losers to realize that momentum trading strategy was profited for short-term period (one month) and long-term period (3-years to 5- years) and reversal trading strategy was profited for medium term (3-month to 1-year).

Hong and Stein (1999) recognize momentum traders as those who condition their trades only on past price changed. This simple trading rule, along with a gradual release of information to news watchers allows for both short-term under-reaction and long-term over-reaction. Hence, if past returns are strongly positive, positive autocorrelation suggests that future stock returns will also be greater than average. Investors can exploit this expectation by buying call options on the market index, thereby creating an upward pressure on call prices. Similarly, if past returns are negative, then future stock returns are projected to be below average. Investors can exploit this expectation by buying put options on the market index, creating an upward pressure on put prices. This is cross-market momentum that the option prices depend on the past manifestation of spot market. Additionally, many researcher consider the momentum trading is common phenomenon for all kinds of financial investment. Hence, if past returns are strongly positive, positive autocorrelation suggests that future stock returns will also be greater than average. Investors can exploit this expectation by buying call options on the market index, thereby creating an upward pressure on call prices. Similarly, if past returns are negative, then future stock returns are projected to be below average. Investors can exploit this expectation by buying put options on the market index, creating an upward pressure on put prices. This phenomenon is cross momentum behavior which past performance transfer to option market.

Second, portfolio insurance consideration suggests that the degree to which market participants want exposure to stock prices can depend on recent stock market movement, which then affects the supply and demand for calls and puts. An easy way of changing the exposure to the stock market is by buying call and put options on a stock market index. If, after market prices have risen, an increased number of market participants demand greater exposure to equities, they can purchase call options on a market index, thereby putting upward pressure on call prices. In this case, all prices rise to increase the supply of call writers.

If, after market prices have fallen, an increased number of market participants demand smaller exposure to equities, they can purchase put options on a market index, thereby putting upward pressure on put prices. In this case, put prices rise to increase the supply of put writers.

Third, past stock returns can change investors' expectations about the higher moments of stock prices. If investors care about higher moments, then their demand for call and put options can change as their expectations about higher moments change, again creating pressures in call and put prices. For example, previous researches in the stock market have found that investors prefer skewness in stock returns. Once again, changes in market momentum can affect the supply and demand for option by changing investor' skewness in stock returns.

For stock and option market, Tavakkol (2000) conceived that all of these study probe the short-term relationship (intra-day and next day), as they focus on quick information transfers across markets. Even though the autocorrelation and cross-correlation studies in equity markets cover longer periods of time, the long-term lead-lag relationships in options and the underlying asset markets have not been investigated. They use Black's (1976) model to calculate implied volatilities and the volatility spread at the end of period t is calculated as the difference between the simple average implied volatility of calls and the corresponding average for puts. The one- to 12-month S&P futures returns are used as momentum variable for spot market. They examined the relationship between option market and spot market by OLS estimates of the regressions of volatility spread on lagged spot market returns and indicated prior one-month and three-month returns on S&P future contracts have explanatory power over volatility spreads observed at the end of the period. This means that buying in the asset market over a one- to three-month period is associated with upward pressure on calls and downward pressure on puts. This positive pressure, triggered by long call and short put trades, increases the implied volatility for calls and lowers the implied volatility for puts, thus reducing the volatility spread at the end of the period, and vice versa. Furthermore, the stabilizing effect of feedback trading is also tested in their study. i.e. , whether the activities in the options market are strong enough to cause a reversal in the underlying market. This result supports the reversion hypothesis and the empirical evidence reported for equity market by Jegadeesh an Titman (1993).

Amin, Coval and Seyhun (2004) adopted the Standard and Poor's 100 Index (also called OEC options) and the market returns are computed using the value-weighted index of NYSE, AMEX, and NASDAQ stocks to investigate the relationship between option market and stock market. At the beginning, they constructed the Boundary Condition Tests Based on Put-Call Parity for American Options. An increase in past stock returns causes the probability of boundary violation to increase and the magnitude of the arbitrage violation is also added. This observation are acknowledged that stock momentum have a significant impact on option market. Next, They formulated a parametric approach instead of the nonparametric boundary condition violations. The parametric measure of the price pressures in option markets is the implied volatility of call and put prices. Implied volatility is computed using the escrowed dividend modification of the binomial model employed in Harvey and Whaley (1992). Similarly, the relationship between option market and stock market are examined. Their finding is like Tavakkol's result that past returns is the pressure for option prices. In addition, They suggested that standard option pricing model and past returns are independent is not correct and there is no perfect arbitrage activities to reach the equilibrium of market price.

3. Data and Methodology

3.1 Data Resources

For this study, three of ETFs and SPX index extracted from the Datastream, Bloomberg, and OptionMetrics. Carrying out 2:1 stock split at 2000/03/20 and matching the maximal period of stock return in this study, the QQQQ ETF is collected during 2001/01/02. Past stock return are computed the preceding 10 days (2 weeks), 20days (4 weeks), 30 days (6 weeks), 40 days (8 weeks), 60 days (12 weeks), 80 days (16 weeks), 100 days (20 weeks), 120 days (24 weeks), 150 days (30 weeks), 200 days (40 weeks) of returns as the momentum factor. The deriving data contains the Security ID, its dividends, dividend rate, trading date, close price, open price, bid price, and the ask price. The end of the researching date is 2007/06/29 and Table 3-1 presents other characteristics of underlying asset.

TABLE 3-1 Basic Characters for SPDR, QQQQ, and DIA

ETF	SPDR	QQQQ	DIA
Tracing Index	S&P 500	NASDAQ 100	DOW JONES
Listed Date	1993/01/29	1999/03/10	1998/01/14
Index for Listed Date	438.78	2038.51	7784.69
Close Price on 2007/6/29	1,503.35	1934.10	13408.62
Return till 2007/6/29	242.62%	-5.12%	72.24%
Contract Size	1/10	1/40	1/100
Expense	0.12%	0.2%	0.18%
Exchange	AMEX,NYSE, NASD	AMEX,NYSE, NASD	AMEX,NYSE, NASD

New York Stock Exchanges is called NYSE, National Association of Securities Dealers Automated Quotation is called NASD, and American Stock Exchange is call AMEX. The NYSE opened three bigger ETF up to trade on July 31, 2001.

ETF options are provided by the OptionMetrics from 1996/01/02 to 2007/06/29. The categories that we download it contains the option type (call or put), its Security ID, trading date, strike price, expiration date, bid price, ask price, trading volume, implied volatility, and the Greeks. The other attributes of ETF option are described on the Table 3-2.

TABLE 3-2 Basic Characters for SPY Option, QQQQ Option, and DIA Option

ETF OPTION	SPY OPTION	QQQQ OPTION	DIA OPTION
Underlying ETF	100 shares of SPDR	100 shares of SPDR	100 shares of SPDR
Listed Date	2005/1/10	1999/03/10	2002/05/20
ETF Price for Listed Date	112.80	50.04	90.55
ETF close price on 2007/06/29	148.20	47.49	131.78
Types of Option	American	American	American
Exchange	AMEX,CBOE	AMEX,CBOE	AMEX,CBOE

CBOE-Chicago Board Options Exchange

3.2 European Options

The implied volatility spread is considered the barometer of option market, so the first thing we should do is to estimate implied volatility of any sort of option contract. In the OptionMetrics database, Most index options have a European-style exercise feature and can be computed according to the Black-Scholes model (Merton,1973). The Black-Scholes model can be written as

$$C = Se^{-qT} N(d1) - Ke^{-rT} N(d2)$$

$$P = Ke^{-rT} N(-d2) - Se^{-qT} N(-d1)$$

where

$$d1 = [\ln(S/K) + (r - q + 1/2\sigma^2)T] / \sigma\sqrt{T},$$

$$d2 = d1 - \sigma\sqrt{T}/2$$

C is the price of a call option, *P* is the price of a put option, *S* is the current underlying security price, *K* is the strike price of the option, *T* is the time in years remaining to option expiration, *r* is the continuously-compounded interest rate, *q* is the continuously- compounded dividend yield, and σ is the implied volatility.

For calculating implied volatilities and associated option sensitivities, the theoretical option price is set equal to the midpoint of the best closing bid price and best closing offer price for the option. The Black-Scholes formula is then inverted using a numerical search technique to calculate the implied volatility for the option. In addition, the interest rate is calculated from a collection of continuously-compounded zero-coupon interest rates at various maturities, collectively referred to as the zero curve. The zero curve used by the option models is derived from BBA LIBOR rates and settlement prices of CME Eurodollar futures. For a given option, the appropriate interest rate input corresponds to the zero-coupon rate that has a maturity equal to the option's expiration, and is obtained by linearly interpolating between the two closest zero-coupon rates on the zero curve.

The option pricing methodology of the OptionMetrics for equity options assumes that the security's current dividend yield (defined as the most recently announced dividend payment divided by the most recent closing price for the security) remains constant over the remaining term of the option. This "constant dividend yield" assumption is consistent with most dividend-based equity pricing models (such as the Gordon growth model) under the additional assumptions of constant average security return and a constant earnings growth rate. Even though the dividend yield is constant, this database assumes that the security pays dividends at specific pre-determined times, namely on the security's regularly scheduled ex-dividend date. In the case of dividends that have already been declared, the ex-dividend dates are known. For dividend payments that are as yet unannounced, the database uses a proprietary extrapolation algorithm to create a set of projected ex-dividend dates according to the security's usual dividend payment frequency.

3.3 American Options

Options that have an American-style exercise feature are priced using a proprietary pricing algorithm that is based on the industry-standard Cox-Ross-Rubinstein (CRR) binomial tree model. This model can accommodate underlying securities with either discrete dividend payments or a continuous dividend yield.

In the framework of the CRR model, the time between now and option expiration is divided into N sub-periods. Over the course of each sub-period, the security price is assumed to move either "up" or "down". The size of the security price move is determined by the implied volatility and the size of the sub-period. Specifically, the security price at the end of sub-period i is given by one of the following:

$$S_{i+1}^{up} = S_i u \equiv S_i \exp\left(\sigma\sqrt{h}\right)$$

$$S_{i+1}^{down} = S_i d \equiv S_i \exp\left(-\sigma\sqrt{h}\right)$$

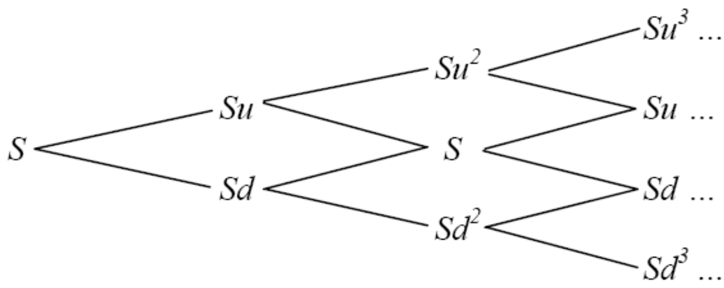
Where $h \equiv T/N$ is the size of the sub-period, and S_i is the security price at the beginning of the sub-period. The price of a call option at the beginning of each sub-period is dependent on its price at the end of the sub-period, and is given by:

$$C_i = \max\begin{Bmatrix} \left[pC_{i+1}^{up} + (1-p)C_{i+1}^{down} \right] / R \\ S_i^0 - K \end{Bmatrix}$$

and likewise for a put option. Here, r is the interest rate, q is the continuous dividend yield (if the security is an index), $R \equiv exp([r\text{-}q]h)$, and C_{i+1} and C_{i+1} are the price of the option at the end of the sub-period, depending on whether the security price moves “up” or “down”. The “risk-neutral” probability p is given by:

$$p = \frac{R-d}{u-d}$$

To use the CRR approach to value an option, we start at the current security price S and build a “tree” of all the possible security prices at the end of each sub-period, under the assumption that the security price can move only either up or down



The tree is constructed out to time T (option expiration).

Next the option is priced at expiration by setting the option expiration value equal to the exercise value: C = max(S−K,0) and P = max(K−S,0). The option price at the beginning of each sub-period is determined by the option prices at the end of the sub-period, using the formula above. Working backwards, the calculated price of the option at time i = 0 is the theoretical model price.

To compute the implied volatility of an option given its price, the model is run iteratively with new values of σ until the model price of the option converges to its market price, defined as the midpoint of the option’s best closing bid and best closing offer prices. At this point, the final value of σ is the option’s implied volatility.

The CRR model is adapted to securities that pay discrete dividends as follows: When calculating the price of the option from equation (1), the security price S_i used in the equation is set equal to the original tree price S_i^0 minus the sum of all dividend payments received between the start of the tree and time *i*. Under the constant dividend yield assumption, this means that the security price S_i used in equation (1) should be set equal to S_i^0 $(1-n\delta)$, where S_i^0 is the original tree price, δ is the dividend yield, and *n* is the number of dividend payments received up to time *i*. All other calculations are the same.

The CRR model usually requires a very large number of sub-periods to achieve good results (typically, N >1000), and this often results in a large computational requirement. The OptionMetrics proprietary pricing algorithm uses advanced techniques to achieve convergence in a fraction of the processing time required by the standard CRR model.

3.4. The Weighting Scheme of Implied Volatility

According to 3-2 and 3-3, we computed implied volatility for every contracts. Each day, for the given set of calls and puts, the implied volatility spread is computed three different ways. The purpose of this exercise is to explore the sensitive of various option to the market momentum hypothesis and ensure that the results are general. The respective weighting schemes are averaging weighted implied volatility (AWIV), vega weighted implied volatility (VGIV), and the elasticity weighted implied volatility (EWIV). We first weight each option implied-volatility equally, averaging across all call and put volatility and taking the difference, resulting in an equally weighted estimate of the implied volatility spread. The concept of AWIV (Trippi, 1977) is that all contracts include the same information and its equation can be written as

$$AWIV = \frac{1}{n}\sum_{j=1}^{n}\sigma_j \tag{3.1}$$

Where

$AWIV$ is the averaging weighted implied volatility, n is the number of observations, and σ_j is implied volatility from jth option contract.

Second, we compute vega weighted volatility spread (Latane and Rendleman, 1976). The vega-weighted spread takes a weighted average of all call and put volatilities based on the partial derivative of each option's price with respect to the volatility. The scheme weights at-the-money options more than out-of-the-money options. If at-the-money options are not affected by market momentum factor, then there should be little or no relation between past stock returns and vega-weighted average spreads. VGIV can be written as

$$VGIV = \frac{\sum_{j=1}^{n}\sigma_j \frac{\partial C_j}{\partial \sigma_j}}{\sum_{j=1}^{n}\frac{\partial C_j}{\partial \sigma_j}} \tag{3.2}$$

Where

$VGIV$ is the vega weighted implied volatility, n is the number of observations, σ_j is implied volatility from jth option contract, and $\frac{\partial C_j}{\partial \sigma_j}$ is the vega value of jth option contract

Our third measure is the elasticity-weighted scheme, which weights by elasticity of each option with respect to the value of the underlying index. This weighting scheme is similar to one used by Chira and Manaster (1978) and incorporates leverage constraints. For example, an investor with limited capital who wishes to gain exposure to directional changes in the stock price typically invests in options with high elasticity. Since the elasticity is decreaing function of how much the option is in the money, this procedure weights out-of-the-money options more than in-the-money options.

$$EWIV = \frac{\sum_{j=1}^{n} \sigma_j \frac{\partial C_j}{\partial \sigma_j} \frac{\sigma_j}{C_j}}{\sum_{j=1}^{n} \frac{\partial C_j}{\partial \sigma_j} \frac{\sigma_j}{C_j}} \tag{3.3}$$

Where

$EWIV$ is the vega weighted implied volatility, n is the number of observations, σ_j is implied volatility from jth option contract, and $\frac{\partial C_j}{\partial \sigma_j} \frac{\sigma_j}{C_j}$ is the elasticity of jth option contract.

We compute the puts implied volatility and calls implied volatility by formula 3.1, formula 3.2, and formula 3.3 and take the difference so that we can obtain implied volatility spread at any period. Table 3-3, table 3-4, and table 3-5 document the sample statistics for the volatility spread averaged for each trading day for each of the three weighting schemes. Notice that ρ1、ρ2、ρ3 are the partial autocorrelation for average daily volatility spreads. All three series exhibit significantly positive, partial serial correlations. The large, positive first-order autocorrelation suggests that the implied volatility spread follows a slow-moving diffusion process. This finding is again consistent with a situation where the innovation in volatility spread arises from sustained price pressure on either call or put options.

Table 3-3 Sample Characteristics of Volatility Spread for SPY Option

Volatility Spread	Equal Weighted	Vega Weighted	Elasticity Weighted
Mean	0.020952	0.017482	0.082124
Median	0.029457	0.024424	0.082436
Maximum	0.180869	0.094689	0.133604
Minimum	-0.128389	-0.061796	0.033229
Standard Deviation	0.039157	0.018625	0.014549
Skewness Coefficient	-0.585828	-1.092192	-0.284532
Kurtosis	4.593568	4.447249	3.842796
ρ1	0.579	0.813	0.92
ρ2	0.24	0.235	0.173
ρ3	0.221	0.236	0.241
Sample Number	622	622	622

This table reports summary statistics of the implied volatility spread as a function of type of weighting for SPY option. The volatility spread is computed as the difference between the implied volatility for call options and the implied volatility for put options (put-implied volatility minus call-implied volatility). A single volatility spread is computed each day by weighting the volatility spreads across all option trades in a given day. The terms ρj denote the partial, autocorrelation coefficients of weighted average volatility spreads at daily lag j.

Table 3-4 Sample Characteristics of Volatility Spread for QQQQ Option

Volatility Spread	Equal Weighted	Vega Weighted	Elasticity Weighted
Mean	0.044379	0.026992	0.09855
Median	0.036298	0.026088	0.09647
Maximum	0.42452	0.182499	0.18837
Minimum	-0.170715	-0.073992	0.04295
Standard Deviation	0.045795	0.01758	0.02475
Skewness Coefficient	0.97082	1.057694	0.74475
Kurtosis	8.387951	10.08739	3.28697
ρ1	0.09	0.3	0.943
ρ2	-0.023	0.159	0.36
ρ3	0.038	0.165	0.254
Sample Number	1631	1631	1631

This table reports summary statistics of the implied volatility spread as a function of type of weighting for QQQQ option. The volatility spread is computed as the difference between the implied volatility for call options and the implied volatility for put options (put-implied volatility minus call-implied volatility). A single volatility spread is computed each day by weighting the volatility spreads across all option trades in a given day. The terms ρj denote the partial, autocorrelation coefficients of weighted average volatility spreads at daily lag j.

Table 3-3 Sample Characteristics of Volatility Spread for DIA Option

Volatility Spread	Equal Weighted	Vega Weighted	Elasticity Weighted
Mean	-0.011081	-0.000219	0.065649
Median	-0.014031	-0.000513	0.064447
Maximum	0.15173	0.065189	0.142913
Minimum	-0.112752	-0.025155	0.011472
Standard Deviation	0.031196	0.008126	0.016244
Skewness Coefficient	0.87761	0.826274	0.666326
Kurtosis	5.581391	7.938271	4.413813
ρ1	0.578	0.607	0.922
ρ2	0.15	0.192	0.186
ρ3	0.058	0.126	0.094
Sample Number	1288	1288	1288

This table reports summary statistics of the implied volatility spread as a function of type of weighting for DIA option. The volatility spread is computed as the difference between the implied volatility for call options and the implied volatility for put options (put-implied volatility minus call-implied volatility). A single volatility spread is computed each day by weighting the volatility spreads across all option trades in a given day. The terms ρj denote the partial, autocorrelation coefficients of weighted average volatility spreads at daily lag j.

3.5 Regression of time series

The empirical model we revise and follow by Tavakkol (2000) and Amin et al. (2004) to examine the relationship between past ETF returns and ETF option price. The regression of time series can be estimated and written as

$$\sigma_{p-c,d,t} = \alpha_1 + \sum_{i=1}^{n} \gamma_i R_{\tau,t-i} + \gamma_0 R_{\tau,t} + \theta_1 \sigma_{p-c,d,t-i} + \sum_{j=1}^{m} \varepsilon_j \tag{3.4}$$

where:

$\sigma_{p-c,d,t}$ = The volatility spread in the current day;

$R_{\tau,t-i}$ = The returns on the ETF in the preceding period;

$R_{\tau,t}$ = The return in the subsequent period (revision);

$\sigma_{p-c,d,t-i}$ = The lagged values of the volatility spread.

τ = The past return period (10, 20, 30, 40, 60, 80, 100, 120, 150, 200 days)

The regression equation 3.4 improve Tavakkol's and Amin's et al. model. First, the volatility spread in the last trading day of the month and the month returns are used on Tavakkol (2000). It is unreasonable to adopt the option closing price of month computed the implied volatility because the implied volatilities and option price is a continuous time series data. It not only delete too much available sample, but also don't consider variations daily, even all the sample data was extracted are the negative relationship. Consequently, we use day to day closing data to displace the monthly data

In addition, Tavakkol's and Amin's et al. model have another ill-considered problem. They do not revise information was happened on that day. They use a 1-day window between the ending day for computing stock returns and the volatility spread to guarantee that potential investors have the necessary information on hand. However, there is a 15-minute time difference between the closing time of the options market 3:15 PM and the closing time of the underlying futures market 3:00 PM, so it must influence implied volatility spread on subsequent spot market. In order to modify this situation, a variable which was the return in the subsequent period was added to revise new information.

If positive feedback traders of the type described by Delong et al. (1990) use the options markets for their speculative trading, then movements in the options market follow price changes in the underlying asset market. On the other hand, if informed traders use the options market transactions, then the options market would lead the underlying security market. To measure price pressures in the options market we use observed implied volatility in the call and put prices. When there is positive news, speculative traders buy calls and sell puts, which causes a positive pressure in the options market by bidding up the call price and putting downward pressure on put prices. A positive pressure will cause the volatility spread to narrow, and a negative pressure will widen it. If momentum traders use the options market, they buy calls and sell puts when the underlying market rises. When the assets market falls, they sell calls and buy puts. The resulting price pressure would induce a negative relationship between lagged returns in the underlying asset market ($R_{\tau,t-i}$) and the volatility spread ($\sigma_{d,t}$) in the options market at time t. Negative γ_1, thus, supports the notion of momentum trading in the options markets.

4. Empirical Result

4.1. Implied Volatility and the Past Stock Returns of ETF

Previous studies suggest that the option pricing models systematically misprices option with respect to moneyness and maturity. Short-term options are typically underpriced by Black-Scholes relative to long-term options. Similarly, deep in-the-money and deep out-the-money options are underpriced relative to at-the-money options. Hence, we need to control for option moneyness and maturities examining the relation between implied volatilities and past stock return of ETF.

We show the implied volatilities of call and put prices as a function of past 40-day stock returns separated by the strike price and maturity of the options (table 4-1, table 4-2, table 4-3, table 4-4). Table 4-1 is the SPY option, Table 4-2 is the QQQQ option, Table 4-3 is the DIA option, and the Table 4-4 is SPX. Panel A shows the implied put volatilities when past 40-day stock returns are positive (greater than 0.05), and panel B shows the implied put volatility when past stock return are negative (less than -0.05). A decline in stock price increases put-implied volatilities regardless of the maturity and strike price. On average, a switch in returns, from 5% to -5%, increases the put-implied volatilities by about 2.34%, from 20.60% to 22.94% on SPY put option. The QQQQ put increases the implied volatilities by about 12.56%, from 34.15% to 46.71%. The DIA put increases the implied volatilities by about 9.41%, from 29.29% to 9.41%. The SPX put increases the implied volatilities by about 5.3%, from 26.21% to 31.51%. As was mentioned above, the more that the underlying component of ETFs are active, the more implied volatility are affected by past return.

Negative stock returns increase implied volatility estimates across the board, while affecting the short-maturity option(1 month or less), deep-out-of-the-money, and deep-in-the-money options the most. For short-maturity puts, implied volatility of SPY option increases from 30.00% to 39.24%, an increase of 9.24 points; while implied volatility of QQQQ option increases from 40.59% to 62.59%, an increase of 22.00% points ; while implied volatility of DIA option increases from 27.09% to 41.65%, an increase of 14.56 points. as compared with short-maturity option, long–maturity are influenced to a smaller extent.

For call options, the patters are similar (panel C and panel D). A shift from rising to declining stock prices increases put-implied volatilities by 1.49%, from 16.11% to 17.60% on SPY call option. The QQQQ call increases by about 11.74%, from 29.72% to 41.46%. The DIA call increases by about 8.50%, from 20.44% to 28.94%. The SPX call increases by about 3.40%, from 26.56% to 29.16%. All implied volatility estimates increase with declining stock prices. Declines in stock prices increase both call and put option volatilities; however, put-implied volatilities increase more than call-implied volatilities (7.4025 more than 6.285). As a result, put option become relatively more expensive when stock prices decline. Given an increase in stock price, investors bid up the relative prices of call option above those of the put options. Given a decline in stock prices, investors bid up the relative prices of puy options above those of the call options.

TABLE 4-1 Implied Volatilities Separated by Call-Puts, Past Stock Returns, Maturity, and Exercise Price for SPY

K*	<0.94	0.94-0.98	0.98-1.02	1.02-1.06	>1.06	ALL
A. Put Implied Volatility when R > 0.05						
M=1	0.2905	0.1697	0.1365	0.2223	0.6440	0.3000
M=2	0.2724	0.1417	0.1151	0.1088	0.2164	0.2252
M=3	0.2554	0.1402	0.1180	0.1061	0.1775	0.2140
M=4	0.2197	0.1494	0.1364	0.1254	0.1467	0.1897
ALL	0.2357	0.1494	0.1314	0.1310	0.2174	0.2060
B. Put Implied Volatility when R < -0.05						
M=1	0.3013	0.2130	0.1842	0.2494	0.7174	0.3924
M=2	0.2908	0.1860	0.1566	0.1357	0.2302	0.2433
M=3	0.2687	0.1805	0.1561	0.1357	0.1975	0.2269
M=4	0.2315	0.1774	0.1639	0.1513	0.1691	0.2015
ALL	0.2510	0.1835	0.1640	0.1582	0.2466	0.2294
C. Call Implied Volatility when R > 0.05						
M=1	0.3770	0.1590	0.1175	0.1207	0.2357	0.2204
M=2	0.2344	0.1360	0.1111	0.0936	0.1440	0.1598
M=3	0.2158	0.1367	0.1163	0.0997	0.1119	0.1543
M=4	0.1948	0.1411	0.1300	0.1195	0.1065	0.1557
ALL	0.2100	0.1415	0.1244	0.1131	0.1219	0.1611
D. Call Implied Volatility when R < -0.05						
M=1	0.3773	0.1978	0.1542	0.1456	0.2493	0.2617
M=2	0.2764	0.1810	0.1508	0.1263	0.1821	0.2049
M=3	0.2300	0.1720	0.1489	0.1281	0.1458	0.1764
M=4	0.1892	0.1647	0.1525	0.1410	0.1232	0.1552
ALL	0.2218	0.1722	0.1518	0.1370	0.1477	0.1760

K* represents the standardized exercised price by dividing the exercise price, K, by the value of the ETF at the time of trade. R is the return on the SPY ETF price from day -40 to day -1. All option maturities between day 1 and day 30 are in M = 1, between day 31 and day 60 are in M = 2, between day 61 and day 90 are in M = 3, and greater than 90 days are in M = 4. All implied volatilities are weighted by the number of trades to compute the averages in each cell. Averages across maturities and exercise prices are equally weighted.

TABLE 4-2 Implied Volatilities Separated by Call-Puts, Past Stock Returns, Maturity, and Exercise Price for QQQQ

K*	<0.94	0.94-0.98	0.98-1.02	1.02-1.06	>1.06	ALL
			A. Put Implied Volatility when R > 0.05			
M=1	0.4356	0.3064	0.2805	0.2870	0.5216	0.4059
M=2	0.3931	0.2857	0.2707	0.2601	0.4860	0.4039
M=3	0.3502	0.2586	0.2456	0.2316	0.3935	0.3467
M=4	0.3437	0.2584	0.2512	0.2416	0.3333	0.3258
ALL	0.3520	0.2682	0.2572	0.2481	0.3692	0.3415
			B. Put Implied Volatility when R < -0.05			
M=1	0.6392	0.5147	0.4863	0.4864	0.7081	0.6259
M=2	0.5461	0.4548	0.4376	0.4282	0.5764	0.5419
M=3	0.5049	0.4157	0.3996	0.3908	0.5398	0.5066
M=4	0.4315	0.3704	0.3624	0.3553	0.4349	0.4247
ALL	0.4701	0.4120	0.3990	0.3915	0.4847	0.4671
			C. Call Implied Volatility when R > 0.05			
M=1	0.4880	0.3086	0.2778	0.2632	0.3230	0.3507
M=2	0.4296	0.2787	0.2653	0.2510	0.2981	0.3327
M=3	0.3644	0.2507	0.2392	0.2255	0.2711	0.2933
M=4	0.3271	0.2455	0.2402	0.2315	0.2754	0.2890
ALL	0.3467	0.2583	0.2487	0.2375	0.2786	0.2972
			D. Call Implied Volatility when R < -0.05			
M=1	0.6581	0.5160	0.4869	0.4792	0.5718	0.5774
M=2	0.5561	0.4530	0.4372	0.4288	0.4665	0.4904
M=3	0.5070	0.4134	0.3983	0.3901	0.4167	0.4434
M=4	0.4253	0.3656	0.3580	0.3517	0.3577	0.3775
ALL	0.4712	0.4087	0.3964	0.3889	0.3887	0.4146

K* represents the standardized exercised price by dividing the exercise price, K, by the value of the ETF at the time of trade. R is the return on the QQQQ ETF price from day -40 to day -1. All option maturities between day 1 and day 30 are in M = 1, between day 31 and day 60 are in M = 2, between day 61 and day 90 are in M = 3, and greater than 90 days are in M = 4. All implied volatilities are weighted by the number of trades to compute the averages in each cell. Averages across maturities and exercise prices are equally weighted.

TABLE 4-3 Implied Volatilities Separated by Call-Puts, Past Stock Returns, Maturity, and Exercise Price for DIA

K*	<0.94	0.94-0.98	0.98-1.02	1.02-1.06	>1.06	ALL
			A. Put Implied Volatility when R > 0.05			
M=1	0.3071	0.1923	0.1581	0.2190	0.4873	0.2709
M=2	0.2724	0.1652	0.1414	0.1410	0.2211	0.2225
M=3	0.2433	0.1553	0.1386	0.1287	0.1754	0.2010
M=4	0.2090	0.1551	0.1434	0.1355	0.1567	0.1813
ALL	0.2307	0.1616	0.1445	0.1468	0.1956	0.1988
			B. Put Implied Volatility when R < -0.05			
M=1	0.4864	0.3434	0.3151	0.3232	0.4740	0.4165
M=2	0.3876	0.3003	0.2793	0.2603	0.2903	0.3120
M=3	0.3576	0.2763	0.2528	0.2357	0.2572	0.2835
M=4	0.3002	0.2561	0.2409	0.2271	0.2217	0.2518
ALL	0.3424	0.2879	0.2684	0.2591	0.2731	0.2929
			C. Call Implied Volatility when R > 0.05			
M=1	0.4765	0.2008	0.1434	0.1486	0.2508	0.3207
M=2	0.3049	0.1655	0.1390	0.1289	0.1715	0.2228
M=3	0.2593	0.1560	0.1377	0.1233	0.1355	0.1985
M=4	0.2137	0.1551	0.1434	0.1357	0.1484	0.1810
ALL	0.2585	0.1626	0.1420	0.1347	0.1577	0.2044
			D. Call Implied Volatility when R < -0.05			
M=1	0.5067	0.3423	0.3035	0.2853	0.3895	0.3803
M=2	0.3953	0.3010	0.2779	0.2563	0.2864	0.3103
M=3	0.3672	0.2791	0.2540	0.2353	0.2564	0.2853
M=4	0.3050	0.2600	0.2440	0.2295	0.2307	0.2573
ALL	0.3484	0.2898	0.2668	0.2494	0.2650	0.2894

K* represents the standardized exercised price by dividing the exercise price, K, by the value of the ETF at the time of trade. R is the return on the DIA ETF price from day -40 to day -1. All option maturities between day 1 and day 30 are in M = 1, between day 31 and day 60 are in M = 2, between day 61 and day 90 are in M = 3, and greater than 90 days are in M = 4. All implied volatilities are weighted by the number of trades to compute the averages in each cell. Averages across maturities and exercise prices are equally weighted.

TABLE 4-4 Implied Volatilities Separated by Call-Puts, Past Stock Returns, Maturity, and Exercise Price for SPX

K*	<0.94	0.94-0.98	0.98-1.02	1.02-1.06	>1.06	ALL
			A. Put Implied Volatility when R > 0.05			
M=1	0.4220	0.2381	0.1821	0.1964	0.6131	0.3363
M=2	0.3332	0.1979	0.1747	0.1677	0.2585	0.2682
M=3	0.3085	0.2000	0.1787	0.1694	0.2040	0.2513
M=4	0.2688	0.2006	0.1903	0.1846	0.1886	0.2383
ALL	0.3076	0.2095	0.1831	0.1813	0.2348	0.2621
			B. Put Implied Volatility when R < -0.05			
M=1	0.5105	0.3282	0.2867	0.2853	0.7437	0.4729
M=2	0.3886	0.2795	0.2526	0.2333	0.3137	0.3212
M=3	0.3596	0.2680	0.2495	0.2351	0.2603	0.2971
M=4	0.3039	0.2508	0.2400	0.2280	0.2222	0.2626
ALL	0.3549	0.2760	0.2559	0.2436	0.3251	0.3151
			C. Call Implied Volatility when R > 0.05			
M=1	0.7336	0.2569	0.1868	0.1724	0.4239	0.4354
M=2	0.3573	0.2011	0.1773	0.1541	0.2246	0.2586
M=3	0.3131	0.2023	0.1802	0.1634	0.1852	0.2367
M=4	0.2652	0.2007	0.1907	0.1838	0.1753	0.2222
ALL	0.3510	0.2144	0.1852	0.1722	0.2088	0.2656
			D. Call Implied Volatility when R < -0.05			
M=1	0.6742	0.3330	0.2842	0.2648	0.4845	0.4536
M=2	0.3974	0.2792	0.2519	0.2287	0.2859	0.3044
M=3	0.3654	0.2698	0.2495	0.2341	0.2596	0.2845
M=4	0.3046	0.2529	0.2413	0.2286	0.2112	0.2413
ALL	0.3730	0.2776	0.2557	0.2393	0.2679	0.2916

K* represents the standardized exercised price by dividing the exercise price, K, by the value of the ETF at the time of trade. R is the return on the SPX ETF price from day -40 to day -1. All option maturities between day 1 and day 30 are in M = 1, between day 31 and day 60 are in M = 2, between day 61 and day 90 are in M = 3, and greater than 90 days are in M = 4. All implied volatilities are weighted by the number of trades to compute the averages in each cell. Averages across maturities and exercise prices are equally weighted.

4.2 Implied Volatility Smiles

Volatility smile refers to the U-shaped implied volatility estimates as a function of the exercise price. Previous option pricing studies have shown that both in-the-money and out-the-money calls and puts have higher implied volatilities than at-the money calls and puts. Moreover, short-maturity options, deep-in-the money calls, and deep-out-of-money puts have the highest estimated implied volatilities, giving rise to a skew-shaped implied volatility. We document a similar relation in table 4-1, table 4-2, table 4-3, and table 4-4. For the puts of ETF, Three ETF and SPX are existed implied volatility smiles whether past stock return are positive or negative. Furthermore, volatility smiles curve moved upward when the decline of stock prices increases volatility for puts . As observed in table 4-1, implied volatility of SPY put increases from 23.57% to 25.10% for out-the-money puts, increasing from 13.14% to 16.40% for at-the-money puts, and increasing from 21.74% to 24.66% for in-the-money puts.

For in-the-money puts, volatility smiles measure is 12.43% (25.57% minus 13.14%) when past stock return are positive. For out-the-money puts, volatility smiles measure is 8.60% (21.74% minus 13.14%). Also, For in-the-money puts, volatility smiles measure is 8.70% (25.10% minus 16.40%) when past stock return are positive. For out-the-money puts, volatility smiles measure is 8.26% (24,66% minus 16.40%).

4-3 ETF Option Prices and Stock Market Momentum

This thesis is computed three weighting scheme of implied volatility. Past studies recommend that there is less mispricing and model error to use at-the-money option. Thus, we focus mainly on the volatility spread computed using vega-weighting. Nevertheless, we also replicated our tests using the two measures as well to examine the relation between past ETF returns and volatility spreads. The cross market momentum hypothesis predicts a negative relation between past ETF return and volatility spreads. Past ETF return are computed using the preceding 10-200 days (2-40 weeks) of close price. In order to guarantees that potential investors have the necessary information on hand to actually implement the tests conducted in this paper, we use a 1-day window between the ending day for computing stock returns distortions. Additionally, we take contemporary return into account to revise that current information from spot market may influences option market.

The properties of the volatility spread suggest a slow-moving time series. Hence, if daily average spreads are used as the dependent variable in ordinary least squares (OLS) regressions, the residuals will exhibit strong autocorrelations, leading to potential biases in the estimated regression coefficients. We need to consider autoregressive model and moving average simultaneously eliminating the correlation structure of the residuals, as judged by the Box-Pierce statistics. Selecting all appropriate model, we choose the best one by coefficient of determination, Akaike information, Schwartz Bayesian information criterion, and the likelihood Ratio test and replicated the tests to examine the effect of past ETF return from 10 days to 200 days. Table 4-5 is the results of the regression of the daily volatility spreads against SPY returns over the past 2 to 40 weeks for the entire sample period. Table 4-6 is the results of QQQQ , Table 4-7 is the results of DIA , and Table 4-8 is the results of S&P 500.

For 10-200 days, the relation between the volatility spread of SPY option and past SPY returns is negative and significant. In addition, that one period lagged is significant positive accords with our observation in table 4-3. For 10-80 days, the relation between the volatility spread of QQQQ option and past QQQQ returns is negative and significant. For 10-120 days, the relation between the volatility spread of DIA option and past DIA returns is negative and significant. In term of our empirical results, for the overall ETFs, the relation between the volatility spread of ETF option and past ETF returns is negative and significant, especially in the underlying component of ETF are more active and the period of significant negative are longer. It also supported cross market momentum hypothesis and existed momentum trading. On the other hand, when the ETF returns in past period are positive, this positive pressure, triggered by long call and short put trades, decrease the implied volatility for calls less than for puts, thus reducing the volatility spread at the end of period. The results is similar to what Tavakkol(2000) examined momentum trading. Namely, when the price of underlying asset increases, the positive feedback traders will trade in option market and expect to profit as a follower. Inversely, the downward movement in the stock market creates a negative pressure (resulting from short call and long put trades), increasing the volatility spread.

TABLE 4-5 Regression of Daily Volatility Spread on Past Market Returns for SPY

$$\sigma_{p-c,d,t} = \alpha_1 + \sum_{i=1}^{n} \gamma_i R_{\tau,t-i} + \gamma_0 R_{\tau,t} + \theta_1 \sigma_{p-c,d,t-1} + \sum_{j=1}^{m} \varepsilon_j$$

Length of Lag	$\sigma_{p-c,d,t-1}$	R_t	R_{t-1}	R_{t-2}	R_{t-3}	Intercept	Adjusted R^2
10(2 weeks)	0.980216 (<0.001)	0.094198 (0.0337)	-0.22821 (0.0015)	0.225944 (0.0017)	-0.11579 (0.0089)	0.000455 (0.0318)	0.7148
20	0.978391 (<0.001)	0.094718 (0.0304)	-0.19264 (0.0088)	0.116262 (0.1129)	-0.03933 (0.3684)	0.00056 (0.0092)	0.7139
30	0.975036 (<0.001)	0.051174 (0.2285)	-0.14507 (0.0417)	0.133164 (0.0614)	-0.05488 (0.0197)	0.000642 (0.0063)	0.7117
40	0.97101 (<0.001)	0.122731 (0.0063)	-0.2804 (<0.001)	0.201727 (0.0081)	-0.05871 (0.1921)	0.00076 (0.0031)	0.7164
60	0.965243 (<0.001)	0.065932 (0.1132)	-0.15564 (0.0302)	0.08378 (0.2417)	-0.00875 (0.8344)	0.000982 (0.0014)	0.7133
80	0.961817 (<0.001)	0.104461 (0.0146)	-0.23122 (0.0015)	0.124612 (0.0853)	-0.01021 (0.8113)	0.001084 (0.0035)	0.7143
100	0.951253 (<0.001)	0.098094 (0.0185)	-0.19148 (0.0066)	0.070823 (0.3124)	0.005531 (0.8954)	0.001561 (0.0005)	0.7164
120	0.949538 (<0.001)	0.053005 (0.2068)	-0.1716 (0.0157)	0.11183 (0.1147)	-0.00867 (0.837)	0.001665 (0.0041)	0.7133
150	0.965175 (<0.001)	0.089014 (0.0322)	-0.18292 (0.0091)	0.062954 (0.3674)	0.024232 (0.5578)	0.001045 (0.0396)	0.7105
200(40 weeks)	0.97613 (<0.001)	0.116063 (0.0038)	-0.17119 (0.0119)	0.045734 (0.4996)	0.00799 (0.8408)	0.000539 (0.1569)	0.7197

This table reports the result of time series regressions of the vega-weighted volatility spread (put-implied volatility – call-implied volatility) versus past 2-week to 40-week market returns. The numbers in parentheses are p-values.

TABLE 4-6 Regression of Daily Volatility Spread on Past Market Returns for QQQQ

$$\sigma_{p-c,d,t} = \alpha_1 + \sum_{i=1}^{n} \gamma_i R_{\tau,t-i} + \gamma_0 R_{\tau,t} + \theta_1 \sigma_{p-c,d,t-1} + \sum_{j=1}^{m} \varepsilon_j$$

Length of Lag	$\sigma_{d,t-1}$	R_t	R_{t-1}	R_{t-2}	R_{t-3}	Intercept	Adjusted R^2
10(2 weeks)	1.050745	0.021136	-0.07353	0.061714	-0.00993	3.77E-05	0.2513
	(<0.001)	(0.1477)	(0.0207)	(0.0523)	(0.0496)	(0.154)	
20	1.048157	0.008217	-0.05242	0.066962	-0.02295	3.88E-05	0.2794
	(<0.001)	(0.5357)	(0.0697)	(0.0205)	(0.0842)	(0.1336)	
30	0.955495	0.004636	-0.04423	0.058044	-0.01906	0.000521	0.2391
	(<0.001)	(0.7548)	(0.153)	(0.0611)	(0.2014)	(0.0365)	
40	1.042602	0.025968	-0.08593	0.083221	-0.02328	4.70E-05	0.2499
	(<0.001)	(0.0762)	(0.0071)	(0.0092)	(0.1151)	(0.0759)	
60	1.052467	0.024464	-0.08277	0.081736	-0.02342	4.33E-05	0.2508
	(<0.001)	(0.0859)	(0.0081)	(0.0092)	(0.1052)	(0.0521)	
80	1.053571	0.020337	-0.08161	0.092381	-0.03107	4.99E-05	0.2514
	(<0.001)	(0.1648)	(0.0122)	(0.0047)	(0.0352)	(0.0332)	
100	1.028504	0.011989	-0.04341	0.03593	-0.00446	9.85E-05	0.2492
	(<0.001)	(0.4221)	(0.1759)	(0.2658)	(0.7703)	(0.0153)	
120	1.045846	0.018142	-0.05658	0.052833	-0.01436	5.69E-05	0.2460
	(<0.001)	(0.2289)	(0.0827)	(0.1051)	(0.3413)	(0.0533)	
150	1.052062	-0.01324	0.000167	0.032456	-0.01936	4.17E-05	0.2464
	(<0.001)	(0.4016)	(0.9962)	(0.3512)	(0.2183)	(0.0226)	
200(40 weeks)	1.043091	0.008079	-0.05148	0.069948	-0.02652	6.11E-05	0.2495
	(<0.001)	(0.5935)	(0.1196)	(0.0345)	(0.081)	(0.0076)	

This table reports the result of time series regressions of the vega-weighted volatility spread (put-implied volatility – call-implied volatility) versus past 2-week to 40-week market returns. The numbers in parentheses are p-values.

TABLE 4-7 Regression of Daily Volatility Spread on Past Market Returns for DIA

$$\sigma_{p-c,d,t} = \alpha_1 + \sum_{i=1}^{n} \gamma_i R_{\tau,t-i} + \gamma_0 R_{\tau,t} + \theta_1 \sigma_{p-c,d,t-1} + \sum_{j=1}^{m} \varepsilon_j$$

Length of Lag	$\sigma_{d,t-1}$	R_t	R_{t-1}	R_{t-2}	R_{t-3}	Intercept	Adjusted R^2
10(2 weeks)	0.858171 (<0.001)	0.029847 (0.0159)	-0.04339 (0.0418)	0.01224 (0.564)	-0.00037 (0.9762)	-2.90E-05 (0.8312)	0.4505
20	0.862235 (<0.001)	0.032983 (0.0026)	-0.05626 (0.0035)	0.02771 (0.1493)	-0.00723 (0.5077)	-1.72E-05 (0.8978)	0.4529
30	0.859839 (<0.001)	0.030829 (0.0143)	-0.04656 (0.0338)	0.015648 (0.4738)	-0.00098 (0.9378)	-2.42E-05 (0.8577)	0.4501
40	0.859304 (<0.001)	0.029816 (0.0146)	-0.05906 (0.0068)	0.031901 (0.1429)	-0.00325 (0.7893)	-2.69E-05 (0.8425)	0.4505
60	0.865259 (<0.001)	0.032518 (0.0056)	-0.04952 (0.017)	0.012529 (0.5455)	0.004982 (0.6705)	-3.98E-05 (0.766)	0.4505
80	0.863319 (<0.001)	0.031913 (0.0082)	-0.05281 (0.0156)	0.014013 (0.5196)	0.008409 (0.485)	-7.20E-05 (0.5914)	0.4508
100	0.860945 (<0.001)	0.031872 (0.0074)	-0.01281 (0.538)	-0.05473 (0.0086)	0.037885 (0.0015)	-8.24E-05 (0.5413)	0.4531
120	0.863693 (<0.001)	0.032768 (0.0051)	-0.04191 (0.0459)	-0.00288 (0.8903)	0.013561 (0.2439)	-7.44E-05 (0.5839)	0.4510
150	0.858078 (<0.001)	0.036334 (0.0013)	-0.03921 (0.0541)	-0.0047 (0.817)	0.007818 (0.4901)	-4.07E-05 (0.7715)	0.4524
200(40 weeks)	0.869929 (<0.001)	0.027627 (0.0123)	-0.01928 (0.3248)	-0.0295 (0.1317)	0.021547 (0.0507)	-5.01E-05 (0.7119)	0.4498

This table reports the result of time series regressions of the vega-weighted volatility spread (put-implied volatility – call-implied volatility) versus past 2-week to 40-week market returns. The numbers in parentheses are p-values.

TABLE 4-8 Regression of Daily Volatility Spread on Past Market Returns for SPX

$$\sigma_{p-c,d,t} = \alpha_1 + \sum_{i=1}^{n} \gamma_i R_{\tau,t-i} + \gamma_0 R_{\tau,t} + \theta_1 \sigma_{p-c,d,t-1} + \sum_{j=1}^{m} \varepsilon_j$$

Length of Lag	$\sigma_{d,t-1}$	R_t	R_{t-1}	R_{t-2}	R_{t-3}	Intercept	Adjusted R^2
10(2 weeks)	0.973096 (<0.001)	-0.03565 (0.0335)	-0.04103 (0.2173)	0.13528 (<0.001)	-0.064087 (<0.001)	0.00024 (<0.001)	0.1851
20	0.975326 (<0.001)	-0.02542 (0.1187)	-0.02724 (0.4135)	0.091366 (0.0061)	-0.039744 (0.0144)	0.000211 (0.001)	0.1795
30	0.975263 (<0.001)	-0.05691 (<0.001)	0.031718 (0.3488)	0.073301 (0.03)	-0.048392 (0.0033)	0.000208 (0.0014)	0.1809
40	0.974504 (<0.001)	-0.05481 (<0.001)	0.024532 (0.4737)	0.080534 (0.0184)	-0.050143 (0.0023)	0.000209 (0.0015)	0.1820
60	0.971913 (<0.001)	-0.02125 (0.177)	-0.03317 (0.3045)	0.100664 (0.0018)	-0.046057 (0.0035)	0.000228 (0.0011)	0.1788
80	0.971164 (<0.001)	-0.03294 (0.0375)	-0.00647 (0.8438)	0.079153 (0.0159)	-0.039594 (0.0125)	0.000235 (<0.001)	0.1790
100	0.970149 (<0.001)	-0.04807 (0.0024)	0.026926 (0.404)	0.071704 (0.0263)	-0.050621 (0.0014)	0.000249 (<0.001)	0.1781
120	0.971473 (<0.001)	-0.02739 (0.0798)	-0.01193 (0.7099)	0.078646 (0.0141)	-0.039489 (0.0115)	0.000242 (<0.001)	0.1773
150	0.97198 (<0.001)	-0.04077 (0.008)	0.015776 (0.6194)	0.059249 (0.0618)	-0.034318 (0.0256)	0.000235 (<0.001)	0.1792
200(40 weeks)	0.97054 (<0.001)	-0.03454 (0.0242)	-0.0058 (0.8525)	0.099339 (0.0014)	-0.059031 (<0.001)	0.000246 (<0.001)	0.1786

This table reports the result of time series regressions of the vega-weighted volatility spread (put-implied volatility – call-implied volatility) versus past 2-week to 40-week market returns. The numbers in parentheses are p-values.

4.4 Robustness Test

4.4.1 Vector Autoregression Model (VAR)

So far, our previous results all indicate that the relationship between implied volatility spread and past ETF returns is significantly negative. Accordingly, We would testify some robustness tests to reinforce our results. First, we use Vector Autoregression Model (VAR) to examine this relationship. The result by VAR, compared to simple time-series regression, has negative relation less significantly (not shown here for brevity). The reasons for this results may be that we cannot adopt the single-lagged variable and the moving average (MA) to eliminate the autocorrelation of residual when using the VAR model. In addition, VAR model cannot estimate the affection for subsequent period; consequently, simple time-series regression is more significant than VAR.

However, the results are estimated by VAR is consistent with simple time-series regression. The relationship between volatility spread and past ETF returns is negative, proved the spot market momentum distinctly affect option prices. It is worth notice that the affection of one-lagged volatility spread to subsequent return is slightly significant, but the relation is positive when the results are significant. This results are also consonant with Tavakkol's (2000) and Jegadeesh and Titman's (1993). If momentum trading is strong enough to reverse the process, then short-term momentum will be followed by a longer-term reversion in the stock market, and speculative activity by momentum traders becomes a stabilizing force. In other words, compared to ETFs, the investing of ETF options which is less familiar for investors would consult past ETF returns. As general mutual funds, investors would choose the excellent underlying asset and care about the performance of past one-month, past three-month, past six-month, and even one year.

4.4.2 Vega-weighted scheme and elasticity-weighted scheme

Nevertheless, we replicated the other two measures (the VGIV and EWIV) as well. While not shown here, we observe the same negative relation between past ETF returns and volatility spreads across the other weighting schemes. Hence, our relations are not produced by a particular weighting scheme.

4.4.3 VXO-weighted scheme (the original-formula VIX)

This study adopted three weighting scheme to compute implied volatility for all contracts also needing to consider two factors. One is the effect of infrequent trading for longer maturity contracts, the other is the time value of option decrease as the maturity is approached. Therefore, we need to control the weighting volatility which have equal basis on maturity. Using VXO formula to weight the implied volatility can solve two considerable factors. The VXO-weighted scheme which is revised is described as follows

$$\sigma_{1C} = \sigma^{X_l,nearC}\left(\frac{X_u - S}{X_u - X_l}\right) + \sigma^{Xu,nearC}\left(\frac{S - X_l}{X_u - X_l}\right)$$

$$\sigma_{2C} = \sigma^{X_l,nextC}\left(\frac{X_u - S}{X_u - X_l}\right) + \sigma^{Xu,nextC}\left(\frac{S - X_l}{X_u - X_l}\right)$$

$$VIX_C = \sigma_{1C}\left(\frac{N_{t2} - 22}{N_{t2} - N_{t1}}\right) + \sigma_{2C}\left(\frac{22 - N_{t2}}{N_{t2} - N_{t1}}\right)$$

$$\sigma_{1P} = \sigma^{X_l,nearP}\left(\frac{X_u - S}{X_u - X_l}\right) + \sigma^{Xu,nearP}\left(\frac{S - X_l}{X_u - X_l}\right)$$

$$\sigma_{2P} = \sigma^{X_l,nextP}\left(\frac{X_u - S}{X_u - X_l}\right) + \sigma^{Xu,nextP}\left(\frac{S - X_l}{X_u - X_l}\right)$$

$$VIX_P = \sigma_{1P}\left(\frac{N_{t2} - 22}{N_{t2} - N_{t1}}\right) + \sigma_{2P}\left(\frac{22 - N_{t2}}{N_{t2} - N_{t1}}\right)$$

Where:

X_u and X_l respectively denote the exercise prices directly above and below current

ETF price, S is the current ETF price level, $\sigma^{X_l,nearC}$ is the implied volatility for near term using X_l, $\sigma^{Xu,nearC}$ is the implied volatility for near term using X_u, $\sigma^{X_l,nextC}$ is the implied volatility for next term using X_l, $\sigma^{Xu,nextC}$ is the implied volatility for next term using X_u σ_{1C} is the near term ATM synthetic implied volatility for calls, σ_{2C} is the next term ATM synthetic implied volatility for calls, σ_{1P} is the near term ATM synthetic implied volatility for puts, σ_{2P} is the next term ATM synthetic implied volatility for puts, VIX_C is VXO-weighted volatility for calls, VIX_P is VXO-weighted volatility for puts, N_{t1} and N_{t2} are the number of trading days until expiry of the near and next term options respectively.

Using VXO-weighted volatility spread and past ETF returns, we find the relationship between option market and spot market is still negative significantly for SPY an DIA (not shown here). The QQQQ is not significant, but it still present the negative relation. As a result, the results are proved that past ETF returns influence ETF option prices certainly, especially for the components of ETF which contain the larger stocks.

4.4.4 Dow Jones Industrial Average and DJX market

In 4-3, we examined ETF-type and non-ETF-type investment of S&P 500 and showed that the relation between volatility spread of SPY options and SPY past returns is significantly negative, but the relation between S&P 500 and SPX is not significant. Therefore, in order to assure the difference between ETF-type and non-ETF-type, we adopt Dow Jones Industrial Average (DJIA) and DJX (the option of DJIA) to reexamine this effect. The result also greatly resembled S&P 500 (not showed here). The investments of ETF-type have the significantly negative relationship, but the investments of non-ETF-type are insignificant. However, we find the DJX volatility spread and short-term DIIA returns have partial significant. The primary cause of the result may be that trading the 30 components of DJIA is easier than trading the 500 components of S&P 500, resulting in the momentum trading of short-term period. As a consequence, whether index is tradable or whether it can use the lowest cost to trade is the essential factor to control when investigating related researches of the option market and the spot market.

4.4.5 Seemingly Unrelated Regression (SUR)

In econometrics, seemingly unrelated regression (SUR), model developed by Arnold Zellner and first published in Zellner (1962), is a technique for analyzing a system of multiple equations with cross-equation parameter restrictions and correlated error terms. An economic model may contain multiple equations which are independent of each other on the surface: they are not estimating the same dependent variable, they have different independent variables, etc. However, if the equations are using the same data, the errors may be correlated across the equations. SUR is an extension of the linear regression model which allows correlated errors between equations. Suppose that the Gauss-Markov assumptions hold for all the equations. Then the OLS estimates are BLUE. However, by using the SUR method to estimate the equations jointly, efficiency is improved. The mathematics is very similar to computing Huber-White standard errors. Suppose we have a series of equations

$$y_i = x_i\beta_i + \varepsilon_i$$

where :

x, β, and ε are vectors and i = 1, ..., M where M is the number of equations. Assume each equation has N observations. Let Σ be an $M \times M$ matrix representing the covariance of residuals between the equations. Even though each equation satisfies the OLS assumptions, the joint model exhibits serial correlation due to the correlation of the error terms. Standard OLS estimation, then, will be inefficient (unless all the equations have the identical explanatory variables). Thus, SUR uses generalized least squares to estimate β:

$$\hat{\beta}_{SUR} = \left(X^{'} V^{-1} X \right) X^{'} V^{-1} Y$$

where

$$V(Y) = \Sigma \otimes I_N$$

where $\otimes$ is the Kronecker product and $V(Y)$ is an $M \times N$ matrix. Once SUR model estimates are obtained, inferences are mainly about testing the validity of cross-equation parameter restrictions.

We realize the economic events happened to affect price for three stock market of U.S. may be relative to each other. In order to solve problem, the last robustness test which we used is SUR model. We adopt the SUR model to reexamine the results of simple time-series regression. Furthermore, we added some variables which can have influence for volatility spread. Expectantly, we fully describe the relationship between option market and spot market momentum. In addition, we lengthen the past returns periods to expectantly observe how long the past ETF returns affect option price. The following is the SUR model of our study.

$$\sigma_{p-c,t,i} = \alpha_{1,i} + \gamma_0 R_{\tau,t,i} + \gamma_1 R_{\tau,t-1,i} + \theta_1 \sigma_{p-c,t-1,i} + \eta \sigma_{s,\tau,t-1,i} + \omega skewness_{t,i} + \lambda pcratio_{t,i} + \varepsilon_{j,i}$$

where:

$\sigma_{p-c,t,i}$ = The volatility spread in the current day for ith market and i = 1, 2, 3.

$R_{\tau,t-1,i}$ = The returns on the ETF in the preceding period.

$R_{\tau,t,i}$ = The return in the subsequent period (revision).

$\sigma_{p-c,t-1,i}$ = The lagged values of the volatility spread.

τ = The past return period (10, 20, 30, 40, 60, 80, 100, 120, 150, 200, 300, 400, 500, 600 days).

$\sigma_{s,\tau,t-1,i}$ = the historical volatility of τ days in the preceding period.

$skewness_{t,i}$ = the skewness coefficient for past τ days.

$pcratio_{t,i}$ = the ratio of puts volume divided by calls volume.

Using the SUR model need to have the same researching period for three markets, because the SPY option is listed on 2005/01/10, the beginning of sample period on other markets are identical. The following five reults are raised from the SUR model. Firstly of all, when adding the one-lagged volatility spread , we observe the Durbin-Watson statistics are close to 2 , abhering to no autocorrelation assumption.

Second, the results in table 4-9, 4-10, and 4-11 indicate that past stock returns continue to show up with negative coefficient against the volatility spread as in table 4-5, 4-6, and 4-7. Hence, including higher moments of stock return distributions does not eliminate the negative relation between past stock returns and volatility spread (γ_1<0). This finding suggests that investors' expectations about future returns directly affect their valuations of ETF options, independent of other channels of influence. This result suggests that (1) past returns do not act as a proxy variable for higher moments of stock return, such as increased volatility, and (2) the market momentum hypothesis is not rejected even when we control for other factors. The results present the volatility spreads of QQQQ are affected significantly by past 120 days return and the volatility spreads of SPY and DIA are affected significantly by past 400 days return. We supposed that the U.S. stock market from 911 Terrorist Attacks to Subprime Mortgage Crisis is the bull market, causing momentum can affect option markets longer. Hence, in this interval, given positive past market returns, investors expect the positive returns to continue, and bid up the prices of call options. Given negative past market returns, investors expect the negative returns to continue, and bid up the prices of put options. We call this the market momentum hypothesis. This hypothesis predicts that past stock returns exhibit an independent positive influence on the volatility spread. Besides, the finance literature documents a negative relation between stock returns and volatility. When stock prices fall, volatility increases. When stock prices rise, volatility decreases. We replicate this finding in table 4-1 to table 4-4. Implied volatilities for puts increase more than implied volatilities for calls, so it cause the negative relationship between volatility spread and past spot returns. Notice that the components of QQQQ are more active, so the momentum trading is not significant for short-term period (120 days). Additionally, the historical volatility and volatility spread turn into the negative relation. It shows price reversal for short-term period on QQQQ and long-term period presents price reversal more easier than other ETF market .

Third, investors' supply and demand for options is not only affected by their return expectations from market momentum, but also by portfolio insurance considerations and both effects are present. When the volatility of stock returns increases, a greater number of investors seek reduced exposure to the stock market and bid up the prices of put options. When the volatility of stock returns decreases, a greater number of investors seek increased exposure to the stock market and bid up the prices of call options. This idea suggests that, if a separate estimate of the volatility is included as a regressor in table 4-9 to table 4-11, it would show up with a positive coefficient (η>0) but would not necessarily drive away the significance of the past stock returns. Both past stock returns and volatility would show up with significant influences.

Fourth, Studies in the stock market have found that both stock returns are right skewed and investors have a preference for (systematic) right skewness. As hypothesized before, we find a positive relation (ω>0) between skewness expectations and the volatility spread. An expectation of increased skewness leads to increased volatility spread. This finding is consistent with a scenario where investors prefer skewness in ETF returns and bid up the call prices when they expect higher skewness. Also, inclusion of the skewness variable does not drive away the effects of past ETF returns or volatility

Fifth, we added the put-call ratio regressor to examine how the volume affected the volatility spread. The results found that only QQQQ has significantly positive relation (λ >0). It presents that when put volume increase more than call volume, causing the put price raise, the call price decline, and the implied volatility spread increase. This result may be due to the QQQQ is quite active, investors prefer the option market to hedge. When the past ETF returns are positive, some investors may establish contrary position which causing the put volume raise and volatility spread increase.

TABLE 4-9 SUR Regression of Volatility Spread on Past ETF Returns, Historical Volatility, Skewness, and Put-Call Ratio for SPY

$$\sigma_{p-c,t,i} = \alpha_{1,i} + \gamma_0 R_{\tau,t,i} + \gamma_1 R_{\tau,t-1,i} + \theta_1 \sigma_{p-c,t-1,i} + \eta \sigma_{s,\tau,t-1,i} + \omega skewness_{t,i} + \lambda pcratio_{t,i} + \varepsilon_{j,i}$$

	α_1	θ_1	γ_0	γ_1	η	ω	λ
10 days	0.001775	0.795151	0.092915	-0.09734	0.208286	0.000715	0.000273
	(0.0894)	(<0.001)	(0.0461)	(0.0333)	(<0.001)	(0.1938)	(0.5541)
20	0.000341	0.771802	0.08993	-0.10464	0.501675	0.002009	0.000396
	(0.8678)	(<0.001)	(0.0586)	(0.0308)	(0.0602)	(0.0072)	(0.4046)
30	-0.00162	0.765266	0.049936	-0.05864	0.878598	0.002029	0.000291
	(0.4904)	(<0.001)	(0.2728)	(0.2101)	(0.0075)	(0.0116)	(0.5379)
40	-0.00267	0.75341	0.122537	-0.13977	1.061912	0.001785	0.000425
	(0.3186)	(<0.001)	(0.011)	(0.0047)	(0.0055)	(0.0541)	(0.369)
60	-0.00365	0.736659	0.052179	-0.08554	1.346369	0.001273	0.000393
	(0.2614)	(<0.001)	(0.2376)	(0.0591)	(0.004)	(0.0757)	(0.4086)
80	-0.0041	0.729553	0.062918	-0.10429	1.492026	0.000659	0.000348
	(0.2968)	(<0.001)	(0.162)	(0.0241)	(0.0083)	(0.3399)	(0.4629)
100	-0.0048	0.707294	0.07992	-0.13363	1.738748	0.000128	0.000429
	(0.3257)	(<0.001)	(0.067)	(0.0029)	(0.0135)	(0.8496)	(0.3633)
120	0.002423	0.698431	0.03954	-0.11691	0.894262	-0.00096	0.000288
	(0.709)	(<0.001)	(0.3663)	(<0.001)	(0.3317)	(0.168)	(0.5402)
150	0.002743	0.738215	0.068964	-0.1338	0.690862	-0.00209	0.000306
	(0.7780)	(<0.001)	(0.1153)	(0.0029)	(0.6203)	(0.0067)	(0.52)
200	0.005542	0.789797	0.088089	-0.12933	-0.05451	-0.00355	0.000334
	(0.6502)	(<0.001)	(0.0381)	(0.0029)	(0.9755)	(0.0118)	(0.4913)
300	0.010628	0.74059	0.091047	-0.15682	-0.19606	-0.00558	0.000323
	(0.5094)	(<0.001)	(0.0317)	(<0.001)	(0.9322)	(0.0134)	(0.4995)
400	-0.02748	0.743278	0.059384	-0.09193	5.144187	-0.00661	0.0004
	(0.027)	(<0.001)	(0.1327)	(0.0206)	(0.0043)	(0.0173)	(0.4104)
500	-0.0243	0.783199	0.00088	-0.02406	4.429177	-0.00813	0.000362
	(0.0041)	(<0.001)	(0.9783)	(0.4586)	(<0.001)	(0.0143)	(0.4662)
600 days	-0.01257	0.772696	0.026571	-0.03938	2.438088	-0.01112	0.000166
	(0.0105)	(<0.001)	(0.3321)	(0.149)	(<0.001)	(0.0044)	(0.7309)

Estimates are from SUR. The p-values for the estimated coefficients are reported in parentheses. Volatility spread is computed from vega-weighted options for each day.

TABLE 4-10 SUR Regression of Volatility Spread on Past ETF Returns, Historical Volatility, Skewness, and Put-Call Ratio for QQQQ

$$\sigma_{p-c,t,i} = \alpha_{1,i} + \gamma_0 R_{\tau,t,i} + \gamma_1 R_{\tau,t-1,i} + \theta_1 \sigma_{p-c,t-1,i} + \eta \sigma_{s,\tau,t-1,i} + \omega skewness_{t,i} + \lambda pcratio_{t,i} + \varepsilon_{j,i}$$

	α_1	θ_1	γ_0	γ_1	η	ω	λ
10 days	0.018747	0.171118	0.055498	-0.08535	0.857291	-0.00056	0.002022
	(<0.001)	(<0.001)	(0.182)	(0.039)	(<0.001)	(0.4184)	(0.0011)
20	0.029787	0.134854	0.054908	-0.10982	-0.21175	0.000109	0.001972
	(<0.001)	(<0.001)	(0.2023)	(0.0114)	(0.4732)	(0.8989)	(0.002)
30	0.03281	0.134072	0.001626	-0.04233	-0.50371	0.000137	0.001772
	(<0.001)	(<0.001)	(0.9696)	(0.3286)	(0.1508)	(0.8908)	(0.0057)
40	0.035661	0.139638	0.076467	-0.11609	-0.82807	0.000004	0.001755
	(<0.001)	(<0.001)	(0.0827)	(0.0092)	(0.0375)	(0.9997)	(0.006)
60	0.043029	0.119864	0.016356	-0.0503	1.51756	0.001755	0.001781
	(<0.001)	(0.0025)	(0.687)	(0.2202)	(0.0014)	(0.1386)	(0.005)
80	0.045964	0.127039	0.059324	-0.08997	-1.87296	0.000724	0.001858
	(<0.001)	(0.0014)	(0.1533)	(0.0315)	(<0.001)	(0.5516)	(0.0032)
100	0.05108	0.109391	0.036434	-0.07353	-2.32308	-0.0004	0.001837
	(<0.001)	(0.0059)	(0.3696)	(0.0712)	(<0.001)	(0.7636)	(0.0033)
120	0.055974	0.113357	0.065536	-0.10067	-2.8572	-0.00062	0.001906
	(<0.001)	(0.0047)	(0.0988)	(0.0113)	(<0.001)	(0.6837)	(0.0022)
150	0.059309	0.097799	0.000437	-0.03557	-3.12238	-0.00354	0.001809
	(<0.001)	(0.0148)	(0.9912)	(0.3727)	(<0.001)	(0.0576)	(0.0037)
200	0.06523	0.074534	0.010112	-0.05792	-3.58812	-0.01612	0.001701
	(<0.001)	(0.062)	(0.7843)	(0.1203)	(<0.001)	(<0.001)	(0.0057)
300	0.048345	0.117642	0.027315	-0.04113	-2.15072	-0.02341	0.001685
	(<0.001)	(0.0031)	(0.4801)	(0.2894)	(0.0089)	(<0.001)	(0.0074)
400	0.029887	0.099876	0.017882	-0.0426	-0.08942	-0.0326	0.001977
	(<0.001)	(0.0123)	(0.6036)	(0.215)	(0.8905)	(<0.001)	(0.0015)
500	0.001734	0.100123	-0.02409	-0.00099	2.939331	-0.02751	0.002041
	(0.7872)	(0.0116)	(0.4022)	(0.9725)	(<0.001)	(<0.001)	(0.0011)
600 days	-0.00048	0.104811	0.006278	-0.01924	2.821549	-0.03773	0.001984
	(0.935)	(0.0081)	(0.7845)	(0.4005)	(<0.001)	(<0.001)	(0.0016)

Estimates are from SUR. The p-values for the estimated coefficients are reported in parentheses. Volatility spread is computed from vega-weighted options for each day.

TABLE 4-11 SUR Regression of Volatility Spread on Past ETF Returns, Historical Volatility, Skewness, and Put-Call Ratio for DIA

$$\sigma_{p-c,t,i} = \alpha_{1,i} + \gamma_0 R_{\tau,t,i} + \gamma_1 R_{\tau,t-1,i} + \theta_1 \sigma_{p-c,t-1,i} + \eta \sigma_{s,\tau,t-1,i} + \omega skewness_{t,i} + \lambda\, pcratio_{t,i} + \varepsilon_{j,i}$$

	α_1	θ_1	γ_0	γ_1	η	ω	λ
10 days	-0.00198	0.589119	0.050005	-0.04206	0.402248	0.000371	0.000316
	(<0.001)	(<0.001)	(0.0952)	(0.1564)	(<0.001)	(0.2957)	(0.3606)
20	-0.00056	0.568494	0.047551	-0.05125	0.200992	0.000385	0.000249
	(0.6527)	(<0.001)	(0.1181)	(0.0996)	(0.2366)	(0.3658)	(0.4869)
30	0.000281	0.565282	0.052102	-0.06743	0.086672	0.000797	0.000335
	(0.8435)	(<0.001)	(0.0812)	(0.0288)	(0.6704)	(0.0693)	(0.3535)
40	0.002261	0.559566	0.043924	-0.07112	-0.21249	0.000414	0.000371
	(0.1674)	(<0.001)	(0.1497)	(0.0238)	(0.3699)	(0.3206)	(0.303)
60	0.003445	0.554523	0.042837	-0.06889	-0.37663	0.000454	0.000444
	(0.0822)	(<0.001)	(0.131)	(0.0186)	(0.1958)	(0.2111)	(0.2183)
80	0.000851	0.550311	0.051391	-0.06572	0.037237	0.000799	0.000458
	(0.7085)	(<0.001)	(0.0729)	(0.0264)	(0.9131)	(0.0247)	(0.207)
100	0.001766	0.53416	0.045446	-0.06981	-0.0603	0.000691	0.000565
	(0.5204)	(<0.001)	(0.1051)	(0.0156)	(0.8846)	(0.0504)	(0.1207)
120	0.010317	0.507535	0.043656	-0.09089	-1.31242	0.000354	0.00083
	(0.004)	(<0.001)	(0.1215)	(0.0018)	(0.0141)	(0.3262)	(0.0221)
150	0.006468	0.531675	0.055865	-0.08566	-0.75475	0.000226	0.000673
	(0.1853)	(<0.001)	(0.0418)	(0.0024)	(0.3076)	(0.5859)	(0.0648)
200	-0.00437	0.544985	0.045034	-0.05928	0.867333	0.00034	0.000563
	(0.5495)	(<0.001)	(0.098)	(0.0328)	(0.4342)	(0.9654)	(0.1267)
300	0.019178	0.520333	0.04797	-0.07475	-2.64819	-0.00033	0.000654
	(0.1212)	(<0.001)	(0.0813)	(0.008)	(0.1583)	(0.8072)	(0.0712)
400	-0.00729	0.518097	0.065813	-0.08089	1.399564	-0.00024	0.000613
	(0.4343)	(<0.001)	(0.0101)	(0.0018)	(0.3139)	(0.8848)	(0.085)
500	-0.00683	0.549201	0.003118	-0.01289	1.339121	0.000633	0.000393
	(0.2769)	(<0.001)	(0.8849)	(0.55)	(0.1497)	(0.777)	(0.2834)
600 days	0.004447	0.55909	0.025647	-0.0234	-0.52201	0.004507	0.000317
	(0.2315)	(<0.001)	(0.1602)	(0.2003)	(0.3045)	(0.0459)	(0.3853)

Estimates are from SUR. The p-values for the estimated coefficients are reported in parentheses.

Volatility spread is computed from vega-weighted options for each day.

5. Conclusion

The purpose of this study is to investigate information transmission between ETF market and ETF option market. In order to examine the existence of momentum trading, the samples of ETF we extracted are SPY, QQQQ, and the DIA, analysed the lead/lag relationship with SPY option, QQQQ option, and the DIA option. In robustness test, we realize that momentum traders use option market to chase the spot market movement, in the mean while, causing the price reversal for future spot market. In long-term period, speculative activity by momentum traders becomes a stabilizing force.

The following this thesis is raised some results. First, in ETF option market, implied volatility for puts is higher than for calls. They all have the conspicuous volatility smiles curve as past ETF returns are positive. On the contrary, while past ETF returns are negative, puts market also has the apparent smiles curve, but calls is not clear or nonexistence. It suggested that puts are typically overpriced relative to calls and interpreted that the strategy of short put is easy to earn profits. The movement of volatility smiles curve shows that past ETF returns have the significant impact on volatility certainly.

Second, the results indicate that returns in the underlying market lead the movements in the options market. Prior 10 days to 200 days returns on SPY ETF have explanatory power (estimated 400 days by SUR model). Prior 10 days to 80 days returns on QQQQ ETF have explanatory power (estimated 120 days by SUR model). Prior 10 days to 150 days returns on SPY ETF have explanatory power (estimated 400 days by SUR model). In terms of QQQQ contracts, if we buy in the asset market over a 10- to 80-days period is associated with upward pressure on calls and downward pressure on puts. This positive pressure, triggered by long call and short put trades, increases the implied volatility for calls more than for puts, thus reducing the volatility spread at the end of the period. Conversely, the downward movement in the stock market creates negative pressure, increasing the volatility spread. This conclusion resembled DeLong et al. (1990), Tavakkol (2000), and Anin et al. (2004). Given the predictive ability of the volatility spread for spot market returns, this spread may be viewed as the barometer of investment sentiment.

Third, we compared the investment of ETF-type with the one of non-ETF-type. the option market of SPDR which is ETF-type is SPY option. the option market of S&P 500 is non-ETF-type is SPX. This research shows that the relationship is significantly negative between past ETF returns and volatility spread for SPDRs and SPY option. In contrast, for S&P 500 and SPX, all of the periods are not significant. Furthermore, for QQQQ option and DJX market, the robustness test is examined to resemble results. This study suggested that whether index are tradable or whether it can use the lowest cost to trade is the essential factor to control when investigating related studies of the option market and the spot market.

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