INDEX PARTICIPATION UNITS AND THE PERFORMANCE OF INDEX FUTURES MARKETS AND INDEX OPTIONS MARKETS

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ABSTRACT

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In response to the need for a simple financial instrument that enables retail investors to easily and quickly participate in the US equity market and for a vehicle that facilitates basket trading by institutions, the American Stock Exchange introduced Standard and Poor' s Depository Receipts (SPDRs) on January 29, 1993.

The purpose of this study is to determine the effects of the introduction of SPDRs on the pricing efficiency of S&P 500 futures market and S&P 500 options market. Using a measure of efficiency that is based on the signed difference between the observed futures price and the theoretical futures price as per the Cost of Carry model, we find that the positive mispricing is reduced when SPDRs are introduced. When the absolute values of the differences are used as the measure of efficiency, the results also show an improvement in the pricing efficiency of the futures markets. Using an ARIMA(4,0,4)-TGARCH(1,1) model, rather than the OLS model, provides us with a more precise test of the mispricing series and supports the findings above. Tests of pricing efficiency of the index options market are conducted by measuring the frequency and magnitude of violations of the no-arbitrage conditions as per the Put-Call Parity. Results from the index options market indicate that arbitrage opportunities do exist but no clear cut conclusion could be made regarding the effect of SPDRs on the index options market. When taking transaction costs into consideration, it is clear that both the frequency and the magnitude of arbitrage opportunities are reduced.

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To my parents, Salem and Mounira

And my Grandma, Bechira

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INTRODUCTION

Most pricing models are developed under the assumption of perfect markets in which arbitrage between the contingent claim and the underlying security is riskless and costless. An arbitrage based model like the Put-Call Parity or the Cost of Carry, derives the theoretical equilibrium value for an option or a futures contract respectively, as part of a specific riskless trading strategy. In a perfect market that strategy will dominate price determination since arbitrageurs will stand ready to take advantage of any possible arbitrage opportunities. In the real world, however, transaction costs, execution problems, and other market imperfections impede the arbitrage needed to maintain the theoretical price structure. The impact of those market frictions is considerably magnified when it comes to index arbitrage. Such arbitrage is difficult to implement, and does not fully eliminate risk. For instance, when pursuing an arbitrage opportunity for the S&P 500 index, a precise number of shares of the component stocks must be bought or sold short. This creates the risk that prices can change on several of the stocks while the arbitrage process is occurring. In fact, it is risk free only if one can execute all of the stock trades at the anticipated price. Delays involved in executing trades on five hundred or more stocks introduce risk by causing the actual traded price to differ from the anticipated price. In addition, odd lots must be traded and both commissions and bid-ask spreads increase the cost of trading. Finally, when the arbitrage strategy calls for taking a short position in the stock, the "uptick rule"[1], the inability to use the proceeds of shares sold short, and limited availability of shares to borrow can introduce additional delays in trading. Instead of trying to replicate the index, index arbitrageurs can design portfolios that closely mimic the index and include as many stocks as required through "basket trading".

Over the past several years, the popularity of "basket trading" has increased with both institutional traders and with retail investors. In general, a basket is a portfolio of stocks that moves with general market trends. The most popular baskets have been those that replicate the performance of some popular market index, such as the S&P 500. Trading baskets of stocks can be difficult and expensive. For example, in stock index arbitrage one must simultaneously take offsetting positions in the stock index future and in every stock in the corresponding index. On the part of retail investors, there has been strong interest in investment products that replicate the performance of an index, such as Vanguard Index 500, an open-ended, no-load mutual fund that attempts to replicate the performance of the S&P 500.

In response to the need for a simple product that both enables retail investors to easily and quickly participate in the US equity market and facilitates basket trading by institutions, PDR Services, a wholly owned subsidiary of the American Stock Exchange, introduced a new investment product: Standard and Poor's Depository Receipts, or SPDRs (pronounced "spiders"). SPDRs began trading on the AMEX on January 29, 1993 with over one million shares trading on the first day. Volume has remained strong with a current average daily volume of over 2.5 million shares[2].

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[1] One barrier to an arbitrage strategy that involves shorting the index in the uptick rule, which prevents investors from shorting the stock on a negative tick of the stock price.
[2] On July 22, 1997, when the Dow Jones Industrial average surged 55 points, trading in SPDRs hit a record high of 4.2 Million shares. See A. Bary, "Well Kept Secrets," Barrons, July 28, 1997, p. 36.

The popularity and success of "basket trading" as witnessed by TIPs[3] and SPDRs led the American Stock Exchange, on March 18, 1996, to introduce the World Equity Benchmark Shares (WEBS) which are portfolios of stocks designed to track the performance of selected Morgan Stanley Capital International (MSCI) country indexes. On June 5, 1997, the Dow Jones & Company proposed to introduce DIAMONDS, an exchange-traded fund based on DJIA. Each of the DIAMONDS will be valued at one-hundredth of the Dow and they are scheduled to begin trading on the AMEX in late 1997[4].

1. Standard and Poor's Depository Receipts: SPDRs

SPDRs are a premier retail security which tracks the overall stock market as represented by the well-known S&P 500 index. Each SPDR represents a claim against a portfolio, administered by State Street Bank & Trust Company of Boston, that approximates the S&P 500 Index. Unlike options, futures, or other derivative securities with a short-term life, SPDRs are tradable equity shares in a 25-year open-ended unit investment trust holding all 500 stocks in the index.

SPDRs have ranked among the top five most actively traded securities by dollar volume on the AMEX since trading began on January 29, 1993. The S&P 500 SPDR has

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[3] TIPs are index participation units that represent an interest in a trust that holds baskets of the stocks in the Toronto 35 Index. TIPs were introduced in March 9, 1990. As of September 1996, $2.5 billion of TIPs were issued and outstanding.

[4] See F. Norris, "After 15 years, Dow Jones Lets Futures Trade on its Average", *New York Times*, June 6, 1997, p. D1.

enjoyed one of the fastest fund launches in history, surpassing $1 billion by the end of 1995 - less than three years from start-up. In comparison, it took Vanguard fund about twelve years to reach $1 billion in assets. With a price at about one tenth the S&P 500 index, SPDRs are as easy to track as they are to trade. In addition to that they are extremely liquid with an extremely tight bid/ask spread of about three cents (1/32). Like many financial instrument prices, SPDR prices are linked to net asset value by an arbitrage mechanism. If the price is more than a few cents above or below net asset value, a dealer will sell the overpriced SPDRs or buy the underpriced SPDRs, buy or sell the underlying stock portfolio, and do a creation or redemption transaction with the trustee. The pricing mechanism is practically identical to the mechanism for stock index arbitrage between the stock market and S&P 500 futures contracts.

Low cost is not the only interesting feature of SPDRs. Like stocks, SPDRs can be owned and traded through an ordinary brokerage account. They can be purchased or sold with market, limit, stop, or stop-limit orders to help individual investors exercise control over their price exposure in entering or exiting the market. SPDRs can be sold short like any individual stock, and are generally eligible for immediate margining under the same terms that apply to common stocks. In addition to that, they are exempt from the uptick rule that requires shares to be sold short only on a plus tick (a price higher than the last sale at a different price). SPDRs also pay dividends quarterly based on the composite yield of the S&P 500.

Like mutual funds, SPDRs give investors overall market exposure through a single investment, which immediately gives diversification across 500 top stock and ninety different industry categories, and eliminates the guesswork in stock picking or sector/theme investing. As Exhibit 1 illustrates, SPDRs provide a number of features that are not available to other mutual funds. Unlike traditional mutual funds or index funds[5], SPDRs are available for purchase or sale during the day like a share of stock (from 9:30 a.m. to 4:15 p.m.), rather than at closing net asset value. If the market were to decline or jump, SPDR holders could execute their trades during the day; mutual fund investors would have to wait until after the close. The difference in entry and exit techniques gives a SPDR's investor more flexibility in timing orders. The combination of the ability to buy or sell at an intraday price and to use any type of stock order gives SPDR investors a wide range of opportunities to reduce their transaction cost and/or to implement any price-sensitive or market-timing strategy. SPDRs' annual expenses are comparable to those of an indexed mutual fund[6]. The ongoing SPDRs' expenses of 18 basis points are cheaper than for most no-load mutual funds. However, brokerage commissions apply when buying or selling SPDRs, and can be viewed as the price to obtain the flexibility to enter or exit the market during the day[7].

SPDRs real advantage is their close imitation of the index. But how closely do the returns of SPDRs match those of the index? Returns are determined by three variables: price change, dividends paid, and reinvestment income. When holding the S&P 500 index, an investor receives dividends at the time of the payment and may immediately reinvest

[5] Index funds are mutual funds, usually open-ended, whose portfolios consist of the same stocks, in the same proportion, as the index itself.
[6] As of March 1997, there is about $2 billion in the trust that holds the S&P securities.
[7] The management fee for the Vanguard Group Index Trust 500 is 20 basis points. This is about 100 basis points lower than the usual fee charged by a mutual fund. Commissions at discount brokers are on the order of $10 for 100 shares of SPDRs, compared to $100 at a full-service house. Total commissions for SPDRs are thus similar to those of a standard mutual fund, even when dealing with a retail broker.

depending on his/her preferences. In contrast, the SPDR trust accrues all dividends received over the course of the quarter, during which time their value is added to the unit price. When the SPDR trust goes ex-dividend at the end of the quarter, its price is reduced to the base cash price of the index. As a result, SPDRs' returns differ somewhat from those of the index.

SPDRs are intended to appeal to both retail investors and institutional traders[8]. SPDRs offer the retail investor a more flexible alternative to an indexed mutual fund. Mutual funds trade only at the end of the day and may not be bought on margin or shorted. With SPDRs, the investor can buy or sell at an intraday price using market, limit, or any type of order available for stocks. The investor can write options against a SPDR and can short a SPDR, even on the down-tick with no minimum purchase account. The cost of this flexibility is that SPDR trades generate brokerage commissions whereas the trades of no-load mutual funds do not. SPDRs offer institutional traders an attractive alternative to basket trading. By using SPDRs, rather than stock, the institutional trader can avoid the delays that increase the risk associated with stock index arbitrage. Also the manager of an equity portfolio may choose to use SPDRs, rather than futures contracts, to reduce the effective cash balances that must be held for liquidity purposes. SPDRs can also be used by managers attempting to keep all of their funds in equities rather than money market instruments. Index funds and portfolios managers who invest in large-capitalization companies to replicate the index need to constantly think about reinvesting dividends and other monies they generate without affecting their investment strategies. It

[8] According to AMEX vice-president Jay Baker, individual, as opposed to institutional investors are responsible for about 35% of SPDR trading volume.

would cost tens of thousands of dollars to buy enough shares of each S&P 500 stock to match the index' weighing. One alternative is to invest in short-term instruments until enough cash is available for a meaningful equity investment. Another alternative would be to invest in SPDRs. The managers keep buying units until they reach a $50,000 market value at which point they can exchange the SPDRs for their underlying stocks.

Exhibit 1: Comparison: SPDRs vs. Typical Mutual Fund

Investment Features	SPDRs	Typical No-Load Mutual Fund
Regulated under Investment Company Act of 1940	Yes	Yes
Assets held by Trustee Bank	Yes	Yes
Immediate Diversification, Professional Administration	Yes	Yes
Market Access	Throughout the Trading Day, 9:30 am - 4:15 pm NY	Forward Pricing Only at 4:00 pm NY
Account Requirements	Ordinary Brokerage Account	Separate Mutual Fund Account
Automatic Dividend Reinvestment Available	Yes (Beginning 1/1/94)	Yes
Minimum Investment	About $45 (1 SPDR)	$2,000
Can Purchase on Margin	Yes	No, marginable only 30 days after purchase.
Can be Sold short	Yes (even on down-tick)	No
Can Write Options Against	Yes (e.g., 1 short SPX call is covered by 1,000 SPDRs)	No
Expense Ratio	19 bps through 1996	30 – 50 bps or more
Brokerage Commissions	Ordinary stock commissions apply	None

Sources: American Stock Exchange
Angel J. J. , D. M. Chance, J. C. France, and G. L. Gastineau, "Comparison of Two Low-Cost S&P 500 Index Funds", *Derivatives Quarterly*, Spring 1996.

2. Implications of SPDRs on stock index futures and stock index options

Before SPDRs were introduced, investors basically had four ways to match the S&P performance. First, they could purchase the entire basket of 500 stocks, which for most individuals is prohibitively expensive and therefore impractical. Second, they could buy futures and options on the index: because these instruments have relatively short lives and pay no dividends, they are used mainly by large institutional investors for hedging and by smaller investors for speculating. A third option was to buy into index funds: the fourth, to invest in the NYSE's "Exchange Stock Portfolio" or AMEX's SuperUnit Trust.

If index participation units, SPDRs in particular, provide more diverse payoffs to investors than the existing securities, the capital market will be more complete. One way to observe any benefits arising from the trading of SPDRs is to test the market efficiency of products based on the index. Stock index options and futures rank among the most remarkable financial innovations the securities markets have witnessed. In particular, a futures contract based on the Standard and Poor's (S&P) 500 Index was launched on April 21, 1982, by the Chicago Mercantile Exchange (CME). This instrument has evolved into the most successful and viable stock index futures contract. Due to the success of this contract, the CME introduced options on the S&P 500 futures on January 28, 1983. The popularity of the S&P 500 index also paved the way to another derivative product. On July 1, 1983, the Chicago Board Options Exchange (CBOE) started trading in S&P 500 (SPX) index option contracts. Noting that these derivative securities are all based on the same underlying asset, the S&P 500 stock index, it is to be expected that they are interrelated with SPDRs. If SPDRs truly make it easy to track the market movement and to arbitrage away any discrepancy between the index and the index products, trading in index products becomes more active. With increased activity, the index futures markets and the index options markets may exhibit more efficiency in revealing price information.

The large daily trading volume of SPDRs coupled with their redemption option may generate increased activity in the underlying 500 stocks. At the same time, SPDRs trading may take away some trading volume from the S&P 500 component stocks if some investors are mainly interested in those stocks for a diversified portfolio that tracks the general market movement. If SPDRs are indeed easily used in index arbitrage, activities of index futures and index options would also rise. However, if SPDRs take away the market indexing functions of, for instance, index futures used in portfolio management, the presence of SPDRs may hamper the activities in the futures market. Since the SPDRs holders receive quarterly dividends, they are not subject to the dividend uncertainty as is the case with index futures and index options holders. Unlike futures, SPDRs do not have to be rolled over and they may be attractive to small investors who cannot afford large denominations associated with index futures. Since SPDRs do not expire and are less volatile than futures, their margin requirements are lower than that of index futures. Finally, several empirical studies show that index futures lead the index in price and volume indicating that investors with new information are more likely to use index futures than the stocks underlying the index. With the presence of SPDRs, such trading information can be shifted from index futures since investors may find the fixed maturity and margin requirement associated with futures unattractive. If SPDRs act as a close substitute for index futures, the volume in the futures markets would decline. On the other hand, if SPDRs create new interest in market indexing and become an easy tool for index arbitrage, the volume in the futures market would be expected to increase.

SPDRs are designed as an alternative to trading S&P 500 stocks and the S&P 500 futures contract. However, that does not necessarily imply that the introduction of SPDRs reduced the volume or efficiency of those markets. Park and Switzer (1995) find that when similar index participation units are introduced into the Toronto market in March 1990, the trading activity of the T35 Futures Contract increased and the trading activity of stocks in the index showed little change. They also find a significant reduction in the discrepancy between prices of the stocks in the index and the price of futures contracts on the index. They suggest that this increased volume and improved efficiency may be attributed to the role index participation units play in facilitating stock index arbitrage.

Of course, results found in Canadian financial markets do not necessarily apply to the US markets. Trading volumes on the S&P 500 futures contracts are very large compared to those of the T35. Moreover, the discrepancy between the prices of the stocks in the S&P 500 index and the price of the futures contract are very small in magnitude (MacKinlay and Ramaswamy, 1988). Given the differences between the markets, the introduction of SPDRs may have a very different effect upon the volume and efficiency of the S&P 500 futures contracts or, perhaps, no effect at all.

The purpose of this study is to examine the effects of SPDRs trading on the index derivatives market, more specifically on the pricing efficiency of index futures and index options contracts. The first part deals with SPDRs and their effects on the index futures market. In the first section, the relevant literature on the subject is reviewed. The second section includes the theoretical framework for index futures valuation using the Cost of Carry Model. Based on this model, a pricing efficiency measure is defined, specifically as the mispricing or the deviation of the actual index futures prices from their theoretical values as suggested by the Cost of Carry model. In the empirical tests, the generated index futures mispricing series are examined before and after the introduction of SPDRs. The mispricing series are then described under different models in order to provide a more rigorous test of mean differences in mispricing than the usual Ordinary Least Square method. The models tested in this study are the ARIMA(4,0,4) model, GARCH(1,1) model, GJR-GARCH(1,1) model, and T-GARCH(1,1) model. Finally, a brief summary and conclusions are provided.

The second part deals with SPDRs and their effects on the index options market. The first section includes an overview on previous relevant empirical studies on index options. In the second section, a theoretical framework for index options valuation using Put-Call Parity is designed. Based on this model's no-arbitrage arguments, three boundary conditions are formulated. Pricing efficiency in this case is measured by calculating the magnitude and the frequency of violations of those boundary conditions. The third section covers the empirical tests on the effects of SPDRs on the index options markets and also the effects of various option characteristics such as maturity and whether the options are out-, at- or in-the-money on the occurrence of violations tested. The fourth section includes the results of tests regarding the nature of the index options market over time. Two hypotheses are tested. The first hypothesis investigates whether the magnitude of a violation decreased in the second half of the testing period. The second hypothesis examines whether the frequency of violations changed after the introduction of SPDRs. In the fifth section, the effect of transaction costs on the results obtained in the previous sections is investigated and the sixth provides summary and conclusions.

This study differs from previous studies in numerous ways. First, a longer and more recent testing period is considered (January 2, 1990 to June 3, 1996). Second, intradaily data on index futures and index options are used. Problems of non-synchronous prices are reduced by using intradaily data and also by considering only trades that occur at the exact same time to the second. Third, so far, this is the first study that investigates the relationship between index participation units and index options. Moreover, the index options analysis controls for some market impediments such as transaction costs and bid-ask spread. Fourth, the mispricing series of index futures are thoroughly investigated by fitting different models and allowing for different distributions in order to provide a rigorous test of the effect of the introduction of SPDRs on the index futures market.

STANDARD AND POOR'S DEPOSITORY RECEIPTS AND THE PERFORMANCE OF THE S&P 500 INDEX FUTURES MARKET

INDEX FUTURES

Stock index futures contracts began trading on February 24, 1982 when the Kansas City Board of Trade introduced futures on the Value Line Index. About two months later, the Chicago Mercantile Exchange introduced its S&P 500 futures contract; by 1986, the latter became the second most actively traded futures contract in the world, with over 19.5 million traded in that year[9]. In May 1982, the NYSE Composite Index futures contract began trading on the New York Futures Exchange. In July 1984, the Chicago Board of Trade gave up on its attempts to trade futures on the Dow Jones Industrial Average (DJIA) and instead, began trading its Major Market Index (MMI) futures contract.

In their short history of trading, stock index futures contracts have had a great impact on the world's securities markets. These instruments have become very useful to both individual and institutional investors. Individual investors have found the stock index futures contracts to be a low-cost and efficient vehicle for trading on expectations of future movements in the equity markets. Before the introduction of stock index futures,

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[9] The 1987 stock market crash caused trading in stock index futures to shrink. Volume in the S&P 500 futures contracts declined to 19.04 million contracts in 1987 and to only 11.4 million contracts in 1988.

investors had to buy and sell large portfolios of stocks in order to be able to trade on broad market movements. The transaction costs of such strategies were extremely high, and their executions were slow. With stock index futures, investors can carry out the same trades by making one simple transaction. In fact, institutional investors have come to rely on stock index futures to hedge their portfolios and to allocate their assets among cash, equity, and long-term debt investments. Nevertheless, stock index futures trading has been accused of making the world's securities markets more volatile than ever before. Critics claim that individual investors have been driven out of the equity markets because the actions of institutional traders, both in the spot and futures markets, cause stock values to fluctuate with no links to their fundamental values. Many market participants and political figures have even called for a ban on stock index futures trading. Whether stock index futures trading is a blessing or a curse is debatable. However, it is certainly true that its existence has revolutionized the art and science of institutional equity portfolio management.

1. The S&P 500 Stock Index Futures:

The S&P 500 index futures contract is traded on the Chicago Mercantile Exchange (CME). To define the dollar size of an index futures contract, the CME gives the contract a nominal value of 500 times the futures index level. The minimum fluctuation in the futures price is 0.05 index points, worth $25 in settlement variation. Therefore, a change of one full point is worth $500 in settlement variation. The contract expires at 3:30 P.M. E.S.T on the Thursday preceding the third Friday of the delivery month. Futures contracts on stock indices are settled in cash and not by delivery of the underlying asset. The final settlement price is based upon the prices of the 500 stocks on the New York Stock Exchange's Friday opening and is set equal to the computed S&P 500 index using those opening prices. This procedure is designed to avoid some of the problems associated with "triple witching hour"; that is when stock index futures, stock index options, and options on stock index futures all expire on the same day. On positions initiated during Thursday's trading session, the settlement variation is computed using the difference between the final settlement price and the trade-initiating price. After payment of this final day's settlement variation, the contract positions are erased from the books.

The following exhibit summarizes some details on the S&P 500 stock index futures contracts.

Exhibit 2: S&P 500 Futures Contract Specification

Contract	Standard and Poor's 500 Index
Exchange	Chicago Mercantile Exchange
Quantity	$500 times the S&P 500 Index
Delivery Months	Mach, June, September, December
Last Trading Day	Thursday prior to third Friday of delivery month
Delivery Specification	Cash settlement according to the value of the index at the opening on the Friday after the last day of trading: if a stock does not open on Friday, its last sale price is used
Minimum Price Movement	0.05 index points, or $25 per contract

LITERATURE REVIEW

Most studies on stock index futures pricing have concluded that arbitrage opportunities do frequently exist for short periods of time. However, arbitrageurs' trades quickly correct the mispricing. For example, if the futures price is too high, arbitrageurs will initiate cash-and-carry arbitrage trades. In the process, their purchase of the underlying security (i.e. the index) will raise stock prices and their sale of the futures contracts will lower stock index futures prices. Hence, equilibrium will be reestablished. To profit from such arbitrage opportunities, investors must be able to trade millions of dollars of stock at low transaction costs.

When Stock index futures first began to trade in 1982, the major puzzle was the persistent and substantial underpricing of futures contracts relative to their theoretical values. The standard Cost of Carry model reflects the equivalence between the forward and futures prices when interest rates are non-stochastic. Since the market interest rates historically exceed the dividend yield on common stocks, one might except that the futures price given by the model will trade at a premium compared to the price of the index. Surprisingly, observations from earlier contracts show that when a futures price is different from its implied theoretical value, such mispricing is usually negative; in other words, the futures contract is trading at a discount.

Cornell and French (1983a, 1983b) attribute this discount primarily to a tax effect which Constantinides (1983) refers to as the "timing option". Stockholders have a valuable timing option because they can reduce their taxes by realizing capital losses and deferring capital gains. In addition, before 1987, such gains could eventually become long-term capital gains subject to lower tax rates. Futures traders, however, do not have this option. All capital gains and losses must be realized either at the end of the year or at maturity of the futures contract; whichever comes first. Thus, a trader who is long in the stock receives not only the cash flows from the equivalent futures portfolio, but also has the opportunity to defer taxes on any realizable capital gains. Because of this tax timing option, stocks may represent a more attractive investment alternative than futures. Therefore, to make the two alternatives equivalent, futures would have to be priced below the theoretical prices as per the Cost of Carry model. The difference represents the value of the tax timing option. However, if the marginal investor is tax-exempt, the timing option would be worthless and the perfect markets' pricing model should work.

Though Cornell's (1985) empirical work does not support the tax timing option hypothesis, his results do not refute the possibility that it may have been at least partially responsible for the underpricing of US stock index futures prices early in their trading history. Instead, Cornell suggests that the early mispricing of stock index futures contracts was a result of traders' early perceptions that futures prices were too volatile. Like Figlewski (1984b) and Peters (1985), he notes that the pricing of stock index futures contracts improved as the markets matured.

Figlewski (1984b) points out that in their first year of trading, stock index futures prices were persistently too low. He shows that approximately 70% of arbitrage opportunities due to mispricings disappear by the close of the following day. He claims that mispricings are due to 'noise' and they will disappear with time as markets mature. Figlewski concludes that the early discounts were "a transitory phenomenon caused by unfamiliarity with the new markets and institutional inertia in developing systems to take advantage of the opportunities presented" (pp. 43). In other words, investors were unfamiliar with the marking to market of stock index futures contracts, uncertain about legal aspects and accounting procedures for futures trading, and unsure about how these contracts should be theoretically priced. As investors became more familiar with these issues, the early discounts disappeared. Stoll and Whaley (1986) and Billingsley and Chance (1988) also support Figlewski's explanation. For instance, Stoll and Whaley (1986) report frequent violations of the model in excess of transaction costs using hourly S&P 500 index and index futures data during the period April 1982 through December 1985. The frequency of violation is nearly 80 percent for the June 1982 contracts; however, for more recent contract maturities, this frequency is below 15 percent. MacKinlay and Ramaswamy (1988) report similar results for the S&P 500 futures contracts expiring in September 1983 through June 1987. Using 15-minute price data, they find that, on average, the Cost of Carry relation is violated 14.4 percent of the time.

Bhatt and Cakici (1990) not only confirm the gradual disappearance of the earlier discount, but they also point out the emergence of a premium. Using daily closing values of the S&P 500 index and its two nearest maturity futures contracts for 1982-1987, Bhatt and Cakici show that: (1) the mispricing is positively and significantly related to time to maturity and dividend yield, rather than being random; (2) futures prices become more efficient relative to the Cost of Carry model price as futures market matured; (3) more contracts sell at a premium than at a discount. The evidence that mispricing increases on average with maturity is consistent with the findings of MacKinlay and Ramaswamy (1988).

MacKinlay and Ramaswamy (1988) employ intradaily data to investigate two scenarios. First, they suppose that the actual futures price exceeds its theoretical price plus the transaction costs involved in performing cash-and-carry arbitrage (which are arbitrarily set at 0.6 percent of the index level) and that the futures price subsequently returns to its equilibrium value. Their results show that it is almost three times more likely that the futures price will again become too high than it is that the futures price will become too low. In the second scenario, MacKinlay and Ramaswamy assume that the S&P 500 futures price falls below its theoretical price and consequently goes back to its equilibrium level. Under these circumstances, they find that it is almost twice as likely that the futures price will subsequently fall below its theoretical price again than it is that the futures price will rise above its maximum value. They attribute these findings to the fact that many arbitrageurs prematurely unwind their positions. Thus, if the futures price is initially too high, arbitrageurs will buy stocks and will sell futures. When the futures price returns to its correct value, they will unwind by selling the stocks and buying back the futures. Consequently, their purchase of futures contracts tends to drive the futures prices higher again and their sale of stocks will lower spot prices as well. The resulting effect is that the upper pricing bound is more likely to be crossed again than is the lower pricing bound.

MacKinlay and Ramaswamy (1988) also document that the variability of futures price changes exceeds the variability of changes in the spot price of the S&P 500 index, even after controlling for the non-synchronous prices in the index quotes. This finding is in contrast to Cornell (1985) who finds that the two variabilities are similar in most cases. The only exception is for the September 1982 contract whereby the variability of the futures price changes exceeded that of the stock index by about 25 percent.

Modest (1984) provides an analysis of the relationship between spot and futures prices in stock index futures market while paying special attention to the impact of dividends and stochastic interest rates. When transaction costs or uncertain future dividends are recognized, he shows that the discounted futures prices can fluctuate within a bounded interval without giving rise to arbitrage profits. Modest also examines the impact of stochastic interest rates and marking to market on equilibrium futures prices. The simulation analysis suggests that these two factors have a minimal effect on equilibrium prices.

Interestingly, foreign stock index futures prices exhibited similar underpricing in their early years. Brenner, Subrahmanyam, and Uno (1989) find that Japanese stock index future sold at a discount relative to their theoretical values during the first two years they traded and that this mispricing declined over time. Yadav and Pope (1990) find that before Great Britain deregulated its financial markets in October (1986), the FTSE-100, an index contract on British stocks trading on the London International Financial Futures Exchange (LIFFE), was also trading at a relatively lower price than its theoretical value.

In contrast, when evaluating the pricing and hedging performance of the stock index futures contract on the Swiss Market Index (SMI), Stulz, Wasserfallen, and Stucki (1990) show that pricing is in accordance with standard principles, allowing no arbitrage profits to be made.

Violations of the Cost of Carry model may appear for a variety of reasons. Some are purely technical. An important one is the infrequent trading of stocks within the index. Consequently, stock index prices, which are averages of the last transaction prices of the component stocks, may not reflect actual developments in the stock market. Lo and MacKinlay (1988) model the effects of infrequent trading on index returns under restrictive assumptions. Assuming that index futures prices instantaneously reflect new information, observed futures returns should be expected to lead observed stock index returns because of infrequent trading of individual stocks even though there is no solid economic significance to this behavior. Another reason for violating the Cost of Carry relation has to do with time delays in the computation and reporting of the stock index value. Once a transaction in the stock market takes place, the transaction information is entered into a computer and transmitted to the particular service that updates and transmits the index level. Three time delays are therefore possible: (a) the delay in entering the stock transaction into the computer; (b) the delay in computing and transmitting the new index value; and (c) the delay in recording the stock index value at the futures exchange. If new information arrives in the stock and futures markets simultaneously and price changes in the futures market are recorded instantaneously, the possible delays mentioned above may cause the futures market returns to lead the stock index returns.

Several papers have analyzed the lead-lag relationship between the stock market and the stock index futures. Most have concluded that the futures market leads the spot market. The lead-time has been estimated to be between five and forty five minutes[10]. Kawaller, Koch, and Koch (1987), for instance, find that the S&P 500 futures prices and the index are simultaneously related on a minute-to-minute basis throughout the trading day. Significant lag coefficients suggest that the lead from futures to cash prices extends for between twenty and forty five minutes, while the lead from cash price to futures prices, though significant, rarely extends beyond one minute. Stoll and Whaley (1990) investigate the time series properties of intradaily returns of stock index and stock index futures contracts. After accounting for the individual stocks' infrequent trading and the bid/ask price effects, they find that S&P 500 and MMI index futures returns lead stock index returns by about five minutes on average and occasionally by as long as ten minutes or more. They also find a weak positive predictive effect of lag stock index returns on current futures returns. This effect has become even smaller as the futures markets have matured.

Another possible explanation for violating the Cost of Carry relation is that an arbitrageur is not allowed to use the total amount of short sale proceeds. Modest and Sundaresan (1983) show that if short sellers of stock cannot use their short sale proceeds, then actually there are no pure arbitrage opportunities implicit in the low stock index futures prices of 1982. This explanation of futures mispricing, however, fails to realize that quasi-arbitrage[11] also serves to enforce the Cost of Carry pricing model. However, and as pointed out by Figlewski (1984), this may explain why a discount is sustained, but it does not explain why a discount came about in the first place. If the actual futures price is higher than the theoretical price, then an arbitrageur would buy the index and sell the futures until equilibrium is achieved. In this case, the problems that arise as a result of short sales would not apply.

Potential impediments to arbitrage include nontrivial transaction costs, the uptick rule in the stock market, limitations on the amount of the short sale proceeds that can be used, and the position limits in the futures market[12]. With such impediments to arbitrage, mispricing of index futures may arise and persist over time. When investigating the efficiency of the market for stock index futures and the profitability of index arbitrage for MMI contracts, Chung (1991) accounts for transaction costs, execution lags, and the uptick rule for short sales of stocks[13]. His results indicate that the size and the frequency of boundary violations are substantially smaller than those reported by earlier studies and

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[10] See Kawaller, Koch, and Koch (1987), Finnerty and Park (1987), Herbst, McCormack, and West (1987), Laatsch and Schwarz (1988), Swinnerton, Curcio, and Bennett (1988), and Stoll and Whaley (1990b).

[11] A quasi-arbitrageur is a trader who begins with a spot position and then moves to an equivalent position superior to the initial one. For example, quasi-arbitrageurs who already own the underlying stocks of the index may find it preferable to sell those stocks out of their portfolios, receive the full proceeds from the sale, and buy index futures contracts. In contrast, pure arbitrageurs would sell the component stocks short and buy index futures contracts if that would lead to an arbitrage profit.

[12] A person shall not own or control more than 10,000 futures contracts net long or net short in all contract months combined.

[13] An arbitrageur attempting to sell short a basket of 500 stocks must wait for an uptick (or a zero uptick) in each of the 500 stocks for an S&P 500 arbitrage. As a result, an arbitrageur may be unable to establish a short position that properly represents the index.

have declined sharply with time for both ex post and ex ante tests. The frequency of violations declines substantially with the assumed level of transaction costs and the assumed length of the execution lag. He also notes that ex ante arbitrage profits are not riskless as evidenced by their large standard deviations and by their substantial differences from mispricing signals. Another interesting result is that the size of arbitrage profits from executable short arbitrages is much smaller and more volatile than that from long arbitrages[14].

Empirical tests of the proximity of stock index futures prices to their theoretical values as per the Cost of Carry model depend to a certain extent on the reliability of the underlying assumptions and the existence of market imperfections. Regarding the assumptions, evidence suggests that the existence of unknown and stochastic interest rates is likely to have an insignificant effect on index futures pricing. Cox, Ingersoll and Ross (1981), French (1982), Jarrow and Oldfield (1981) and Richard and Sundaresan (1981) have theoretically shown that stochastic interest rates can cause disparity between forward and futures prices. In contrast, Cornell and Reinganum (1981), Elton, Gruber, and Rentzler (1982), and Rendleman and Carabini (1979) suggest that the difference is not significant. Although no direct empirical tests are available for the S&P 500 futures contracts, Cornell (1985) suggests that the effect is not likely to be significant for S&P 500 futures due to the low correlation between the index price changes and the changes in the short term interest rates. Bailey (1989) compares the pricing models with stochastic

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[14] When the futures actual price is higher than its theoretical value, a "long arbitrage" can be conducted by buying the stocks underlying the index and shorting futures contracts. If the futures price is less than the theoretical price, profits can be made through "short arbitrage", that is, shorting the stocks underlying the index and taking a long position in futures contract.

and non-stochastic interest rates for the Japanese stock index futures, and concludes that the more complex model provides no improvement over the Cost of Carry model. Bailey attributes this finding to the low variance of Japanese interest rates. Cakici and Chatterjee (1991) show, however, that the stochastic interest rate model may give significantly different and substantially better prices compared to the non-stochastic interest rate model. On the other hand, the uncertainty associated with the dividends over the life of an index futures contract significantly affects the formidability of correctly specifying a normative price for index futures contracts. The problem stems from the facts that the numerous dividends associated with indices are difficult to estimate without error and that the appropriate discount rates to apply against these dividends are most of the time even more difficult to estimate. Indeed, the necessity to estimate dividends makes the arbitrage argument itself invalid. Sunders and Mahajan (1988) propose an arbitrage model of index futures pricing which does not require the estimation of dividend uncertainties and controls for the influence of non-synchronous pricing for index futures and spot index values. Their results are consistent with the proposed model implying that as the index futures market has matured with the passage of time, systematic and significant arbitrage opportunities have disappeared. The observed correlation between daily index futures prices and daily spot index values is consistent with market efficiency and supports efficiency of the index futures market.

Until June 19, 1987, stock index futures, index options, and individual stock options all expired at the same time of the same day four times a year (in March, June, September, and December). On these "triple witching days", the exchanges, particularly the NYSE, were drowned with trade orders at the close of the day. Large last-minute trading volumes occurred and were caused mainly by investors placing "market on close" orders to unwind the arbitrage positions they have entered into previously. Some critics claimed that the stock market experienced a large amount of volatility because of these trades, particularly if the majority of the shares involved were on one side of the market. If the futures price was more often too high than it was low during the previous month or two, then arbitrageurs bought stock and sold futures. Most or all of the arbitrage unwinding would probably then involve stock selling. If the futures price was below its theoretical value much more often than it was above, then most or all of the market on close orders would be to buy stock. However, Stoll and Whaley (1986a) and Merrick (1989 find that predicting which way the market will move on expiration day closings is not possible. Merrick (1989) and MacKinlay and Ramaswamy (1988) suggest that such predictions are made impossible due to the unwinding and/or rolling over of previously placed arbitrage trades to the delivery date probably. As a direct result of those concerns, the Chicago Mercantile Exchange in 1987 decided to alter settlement procedures for the S&P 500 futures. Expiration procedures were revised in an attempt to reduce spot expiration day volatility. Instead of expiring at the close of trading on the third Friday of the delivery month, the S&P 500 contract now has a final settlement based on a special opening quotation for the spot of S&P 500 index at the start of trading on the third Friday[15]. Thus, trading ceases at the close of the Thursday before the third Friday. Herbst and Maberly (1990) investigate whether the CME decision has been effective. They find

[15] Prior to June 15, 1984, the last day of trading for the S&P 500 stock index futures contract was the third Thursday of the delivery month, and the last mark to market was based on the last spot S&P 500 index value on that day. From June 15, 1984 until March 20, 1987, the last trading day was the third Friday of the delivery month.

that on a close-to-close basis, no substantive change in volatility has occurred due to the change in settlement procedures. However, the observed decrease in triple witching hour volatility associated with the new settlement procedures coincides with an approximately equal increase in first hour volatility. They concluded that the volatility increase was transitory; a move in one direction at the close of trading on a triple witching day was usually reversed on the next Monday.

THE THEORETICAL FUTURES PRICE AND THE MISPRICING OF INDEX FUTURES

The conventional approach to the valuation of commodity futures is the theory of storage (See Fama and French, 1987). In a perfect market, the futures price for a non-dividend paying stock must equal the deferred value of the current stock price,

$$F^{c}_{(t,T)} = P_t e^{r(T-t)} \tag{1}$$

where $F^{c}_{(t,T)}$ is the futures price at time t for a contract that matures at time T, P_t is the index at time t times the multiplier specified in the index futures contract, and r is the risk free interest rate. The Cost of Carry for a non-dividend paying stock is equal to the interest rate. Therefore, if the futures price does not equal the deferred value of the stock price, traders can form a riskless arbitrage portfolio - making no investment and yet receiving a guaranteed profit. If the futures price exceeds the cost of purchasing the stock

Adding dividends to the model reduces the futures price. Again, compare an investor who purchases the stock at time t with an investor who uses a futures contract to purchase the stock at time T. The stockholder pays P_t at time t. At time T, he owns one share of stock worth P_T. In addition, he owns the dividends, $D_{t,T}$, that have accumulated over the investment period. The futures trader buys one futures contract and invests P_t in bonds at time t. At time T, he receives P_T - $F_{(t,T)}$ from the contract and $P_t e^{r(T-t)}$ from the bonds. The stockholder and the bondholder make the same initial investment, P_t. Assuming that dividends are known at beforehand, these investors bear the same risk. Therefore, their portfolios must have the same terminal values,

$$P_t + D_{(t,T)} = P_t - F^e_{(t,T)} + P_t e^{r(T-t)} \tag{2}$$

Rearranging this equation yields

$$F^e_{(t,T)} = P_t e^{r(T-t)} - D_{(t,T)} \tag{3}$$

The second term on the right hand side is the cumulative value of the dividends paid over the remaining life of the contract, assuming reinvestment at the riskless interest rate. The futures price equals the deferred value of the current stock price minus the deferred value of the dividends that will be paid over the contract period. This equation is enforced by cash-and-carry and reverse cash-and-carry arbitrage between the stock and the stock index futures markets. If at time t, the index futures price exceeds its theoretical price, an arbitrageur can earn a cash-and-carry arbitrage profit by: (1) buying the portfolio that mimics the index, (2) borrowing to finance the portfolio purchase, and (3) going short the index futures. Between t and T, the arbitrageur collects the dividends on the portfolio and invests them until time T. When the futures contract matures, the arbitrageur (1) sells the portfolio, (2) repays the borrowed funds, (3) closes out the futures using cash settlement, and (4) obtains proceeds from invested dividends. Similarly, if the futures price is less than its theoretical price, one can make profit through reverse cash-and-carry arbitrage[17]. Thus, arbitrage profits can be calculated as the mispricing or the deviation of the actual index futures prices from their theoretical values. The mispricing in the futures contract is defined by the following equation:

$$x_t = (F_{(t,T)} - F^{e}_{(t,T)})/\ P_t \tag{4}$$

where F(t,T) is the actual index futures price.

Cornell and French (1982) examine the special case of a stock with a constant dividend yield d. They show that the futures price for this stock can be approximated by

$$F_{(t,T)} = P_t e^{(r-d)(T-t)} \tag{5}$$

[17] At time t, (1) sell short the portfolio that mimics the index, (2) lend the proceeds from the portfolio sale, (3)go long the index futures. Between t and T, borrow to pay dividends on the portfolio. At time T, (1) buy the portfolio and cover the short positions, (2) receive proceeds from the loan, (3) close out the futures using cash settlement, and (4) pay back loans taken out to pay dividends.

The idea behind Equation (5) is straightforward. Dividends partially offset the interest cost of carrying stock. An arbitrageur who purchases the stock and carries it until the futures contract matures, foregoes the interest on his funds, but he receives the dividends from the stock. With a constant dividend payout, the Cost of Carry is approximately equal to the difference between the interest rate and the dividend yield. Therefore, the futures price equals the spot price grossed up by this difference. Note that in this formulation the riskless rate of interest and the dividend yield on the underlying stock index are assumed to be known-constant-continuous rates.

The mispricing expression that corresponds to equation (6) is defined as follows:

$$x_t = \ln F_{(t,T)} - \ln P_t - (r-d)(T-t) \tag{6}$$

The Cost of Carry model takes no account of marking to market of the futures, essentially treating it as a forward contract. Although the theoretical importance of marking to market has been discussed[18], efforts to determine the economic significance of this factor suggest that it is rather small[19]. Another factor left out of this model is the value of the tax timing option discussed by Cornell and French (1983). If a deviation from the equilibrium futures prices is simply due to noise, arbitrage trading should tend to bring it back into line. But if mispricing is the result of specific factors like the tax timing option, it should persist over long periods. Whether and how quickly the basis moves toward its theoretical level can yield some insight into the causes of futures mispricing.

[18] See Richard and Sundaresan (1981) or Cox, Ingersoll, and Ross (1981), for example.

[19] See Elton, Gruber, and Rentzler (1983) or Hill, Schneeweis, and Mayerson (1982).

Index arbitrages are similar to stock arbitrages except that they require the arbitrageurs to buy or short an entire portfolio of stocks and account for the dividends on that portfolio. One approach for buying and selling stock portfolios is to design portfolios that closely mimic the index underlying the futures but include fewer stocks than the index. This technique, however, introduces basis risk into the trade if the mimicking portfolio does not move directly with the index. Program trading instead, allows arbitrageurs to place orders in many stocks simultaneously and thus to reduce the risk that only part of a portfolio will be bought or sold. However, after the introduction of index participation units, index arbitrageurs in the index futures markets do not need to worry about mimicking the index underlying the futures or figuring out what orders to place through the DOT system. One way to test the effect of these index participation units is to look at the mispricing series or the deviations of the index futures prices from their theoretical values. A comparison of the mispricing series before and after the introduction of IPUs may shed more light on the economic role of those new financial instruments. If SPDRs create new interest in market indexing and become an easy tool for index arbitrage, the index futures price is expected to adjust better to its theoretical value after the introduction of SPDRs. The average mispricing in the second half is expected to be lower than the average deviations in the first half.

DATA

The data in this study are from the "time and sales" files for the S&P 500 index futures market for January 2, 1990 to June 3, 1996. These files, provided by the Chicago Mercantile Exchange (CME), consist of the price and time (recorded to the second) of every nonzero price change. For each day in the sample period, we use the nearby Chicago Mercantile Exchange (CMER) S&P 500 futures contract to estimate the mispricing as defined by equation (6)[20]. The S&P 500 futures trade till 4:15 p.m. E.S.T. whereas the S&P 500 closes at 4:00 p.m. To synchronize the trading time of the price series, we match the end of day quotations for the S&P 500 Index with the 4:00 p.m. E.S.T. futures prices. A daily dividend series for the S&P 500 was obtained from Standard and Poor's 500 Information Bulletin. Actual dividend yields are used for equation (5). Daily three- and six-month Treasury Bill rates are used for the riskless rate of interest. The daily data set consists of 1584 observations.

Because a contract loses most of its open interest with hedgers unwinding their positions and the mispricing becomes negligible in the final week, another data set is constructed where the nearby contracts are rolled over to the next contract one-week before expiration.

[20] Equation (3) and (5) provide upwardly biased estimates of the futures price because they omit the effects of daily marking-to-market. As a result, there will be a negative bias in the mispricing estimates generated by equation (4) and (6). We have ignored these biases because they are generally presumed to be very small (Hill. Schneeweis, and Mayerson (1982), Elton, Gruber, and Rentzler (1984), and Cornell and French (1983)). Moreover, there is no reason to assume that the size or direction of these biases will be related to the introduction of SPDRs.

Many empirical studies have examined intraday patterns of index futures and stock price changes; however, little empirical analysis of the intraday co-movement of the prices of index futures and stocks in more normal[21] and recent periods has appeared. Stoll and Whaley (1986), (1987) examine minute-by-minute price change behavior of the S&P 500 and Major Market Indexes in the days surrounding the expirations of the S&P 500 and MMI futures contracts, but do not examine non-expiration days. Kawaller, Koch, and Koch (1987a), (1987b) use intraday data to examine price changes of the S&P 500 index futures; however, they examine only three quarters of the data and do not correct for infrequent trading. MacKinlay and Ramaswamy (1988) also use intraday data, but they focus on deviations from the Cost of Carry equilibrium. Ng (1987) uses intraday data to investigate the price behavior of the S&P 500 index futures prices and its ability to predict the S&P 500 Index level. Chan, Chan, and Karolyi (1990) use intraday price data to examine the transmission of volatility between the stock and index futures markets.

In this study, a longer and more recent time interval (1990 to 1996) is considered. Only trades of the S&P 500 index futures and stock index, occurring at the same time, to the second, are selected. Again, the S&P 500 index futures trades occurring after 4:00 p.m. E.S.T were not considered since the S&P 500 closes at 4:00 while the index futures continue trading till 4:15. This will rule out any errors due to a non-synchronous sample. When examining the characteristics of a time series, it is desirable to use data measured at fairly fine intervals of time. In this case, the data set consists of the last transaction trade recorded at the end of each hour. The intraday data set includes 11088 observations from

[21] Most empirical studies deal with periods where index futures were first introduced or include the market crash of 1987; two factors that might affect their findings enormously.

January 2, 1990 to June 3, 1996. The daily TB rates and dividend yields are assumed to be continuous and constant intraday.

MISPRICING RESULTS

Similar to MacKinlay and Ramaswamy (1988) and Bhatt and Cakici (1990), we find the average mispricing of S&P 500 Index futures is significantly positive, but very small in magnitude. The positive value implies that the market price was, on average, higher than the Cost of Carry model value. The summary statistics on the average daily mispricing are reported in Table 1[22].

MacKinlay and Ramaswamy find that mispricing increases on average with maturity. The average maturities of the futures before and after January, 1993 are compared to assure that the maturities of the futures within the two periods are comparable. As Table 1 shows, the average daily and average intradaily days to maturity are not different between the first half and the second half of the testing period. However, the average daily mispricing of S&P 500 index futures decreases significantly in the second half.

If the Cost of Carry model produces the true futures value, the difference between the market and model prices represents the possible profit to an arbitrageur using the model. The average absolute value of the mispricing gives the average size of the available arbitrage profit. Table 1 shows that the absolute value of mispricing decreases in the second half but not significantly. However, the variability of mispricing is substantially smaller during the second time interval. The decrease in the value and the variability of mispricing implies that after the introduction of SPDRs, market prices of S&P 500 index futures are much closer to their theoretical values as calculated by the Cost of Carry model.

Table 1.a: Summary Statistics on the Daily Differences between Actual and Theoretical Futures Prices: Jan. 90 – Jun. 96.

	Jan. 90 – Jan. 93	Feb. 93 – Jun. 96	Jan. 90 - Jun. 96
Number of Observations	759[a]	825	1584
Average Mispricing	0.319	0.124	0.217
(x 10^{-3})	(1.298)	(1.214)	(1.258)
t-stat. for H0: mean = 0	6.761*	2.924*	6.864*
Average Absolute Mispricing	1.008	0.944	0.974
(x 10^{-3})	(0.878)	(0.773)	(0.825)
t-stat for H0: mean = 0	31.628*	35.080*	47.002*
Average days to Maturity	0.1237	0.1221	0.1228
	(0.0712)	(0.0705)	(0.070)

Standard deviations are in parentheses

* t-stat for mean equal to zero is significant at the 1% level of significance

a The sample includes January 1993.

Table 1.b: Summary Statistics on the Intradaily Differences between Actual and Theoretical Futures Prices: Jan. 90 – Jun. 96.

	Jan. 90 – Jan. 93	Feb. 93 – Jun. 96	Jan. 90 - Jun. 96
Number of Observations	5313[a]	5775	11088
Average Mispricing	0.339	0.080	0.204
(x 10^{-3})	(1.259)	(1.134)	(1.203)
t-stat for H0: mean = 0	19.634*	5.392*	17.901*
Average Absolute Mispricing	0.995	0.890	0.940
(x 10^{-3})	(0.843)	(0.708)	(0.777)
t-stat for H0: mean = 0	86.030*	95.512*	127.354*
Average days to Maturity	0.1237	0.1221	0.1228
	(0.0712)	(0.0705)	(0.070)

Standard deviations are in parentheses

* t-stat for mean equal to zero is significant at the 1% level of significance

a The sample includes January 1993.

[22] Summary Statistics on Daily and Intradaily mispricing for rolled over contracts are reported in the appendix: Table 1a.

The first hypothesis tested examines whether the average mispricing value has changed after the introduction of SPDRs. If SPDRs are an easy tool for index arbitrage, the pricing efficiency of index futures contracts should increase. The null hypothesis in this case is that there is no change between the first half and the second half average mispricing, and the alternative hypothesis is that the magnitude of mispricing has been reduced. Looking at the hypothesis testing results reported in Table 2[23], we can see that the null hypothesis is rejected for the daily signed mispricing. The average daily difference between actual and theoretical futures prices has significantly decreased in the second half of the testing period. The null hypothesis could not be rejected when comparing the average absolute mispricing of the first half and the second half. When examining the intradaily mispricing data, the null hypothesis was rejected for both the signed and absolute value series. Index futures prices seem to conform much better to their Cost of Carry theoretical values after the introduction of SPDRs. It is proven that index futures contracts are priced more efficiently after the introduction of SPDRs. Even though mispricing was reduced, it is not totally eliminated. The positive average mispricing is small but still significant.

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[23] Difference in means and difference in variance tests for rolled over contracts are presented in Appendix 1 Table 2a.

Table 2.a: Daily Difference In Means and Variances

Average Mispricing:

	N	Mean	Std Dev	Std Error	Minimum	Maximum
Before	759	0.00031861	0.00129819	0.00004712	-0.00567163	0.01081758
After	825	0.00012359	0.00121382	0.00004226	-0.00678787	0.00352526
Variances	**T**	**DF**	**Prob>|T|**			
Unequal	3.0810	1547.0	0.0021			
Equal	**3.0896**	**1582.0**	**0.0020**			

For H0: Variances are equal, F' = 1.14 DF = (758,824) Prob>F' = 0.0588

Absolute Average Mispricing:

	N	Mean	Std Dev	Std Error	Minimum	Maximum
Before	759	0.00100761	0.00087768	0.00003186	4.0270E-06	0.01081758
After	825	0.00094370	0.00077267	0.00002690	8.5744E-07	0.00678787
Variances	**T**	**DF**	**Prob>|T|**			
Unequal	**1.5328**	**1515.5**	**0.1255**			
Equal	1.5409	1582.0	0.1235			

For H0: Variances are equal, F' = 1.29 DF = (758,824) Prob>F' = 0.0003

Average Maturity

	N	Mean	Std Dev	Std Error	Minimum	Maximum
Before	759	0.12373934	0.07118616	0.00258389	0.00274000	0.26027000
After	825	0.12208600	0.07051495	0.00245502	0.00274000	0.26027000
Variances	**T**	**DF**	**Prob>|T|**			
Unequal	0.4639	1568.5	0.6428			
Equal	**0.4641**	**1582.0**	**0.6427**			

For H0: Variances are equal, F' = 1.02 DF = (758,824) Prob>F' = 0.7894

Table 2.b: Intradaily Difference In Means and Variances

Average Mispricing:

	N	Mean	Std Dev	Std Error	Minimum	Maximum
Before	5313	0.00033925	0.00125944	0.00001728	-0.01596300	0.01081800
After	5775	0.00008046	0.00113402	0.00001492	-0.00691500	0.00439000
Variances	**T**	**DF**	**Prob>|T|**			
Unequal	**11.3352**	**10710.0**	**0.0001**			
Equal	11.3847	11086.0	0.0000			

For H0: Variances are equal, F' = 1.23 DF = (5312,5774) Prob>F' = 0.0000

Absolute Average Mispricing:

	N	Mean	Std Dev	Std Error	Minimum	Maximum
Before	5313	0.00099511	0.00084312	0.00001157	0	0.01596300
After	5775	0.00088959	0.00070779	0.00000931	0	0.00691500
Variances	**T**	**DF**	**Prob>|T|**			
Unequal	**7.1055**	**10408.0**	**0.0001**			
Equal	7.1570	11086.0	0.0000			

For H0: Variances are equal, F' = 1.42 DF = (5312,5774) Prob>F' = 0.0000

Average Maturity

	N	Mean	Std Dev	Std Error	Minimum	Maximum
Before	5313	0.12375378	0.07112821	0.00097583	0.00274000	0.26027000
After	5775	0.12210355	0.07046500	0.00092725	0.00274000	0.26027000
Variances	**T**	**DF**	**Prob>|T|**			
Unequal	1.2259	10991.4	0.2203			
Equal	**1.2264**	**11086.0**	**0.2201**			

For H0: Variances are equal, F' = 1.02 DF = (5312,5774) Prob>F' = 0.4856

The second hypothesis looks at the change in variability of the mispricing series. If the index futures market is more efficient, then the deviation between the theoretical and actual prices should narrow. This can be tested by comparing the variances of the daily mispricing series for before and after the introduction of SPDRs. The null hypothesis would be that the variances are the same and will be tested against the alternative hypothesis that the variance of the mispricing series in the second half is smaller than that in the first half. Results are presented in Table 2. Again, the findings are in favor of the alternative hypothesis implying that deviations from the Cost of Carry prices, are smaller after the introduction of SPDRs. The same results are discovered when the equality of variance test is conducted on the intradaily mispricing series.

1. OLS estimates

The following expression provides the standard OLS model for the mispricing series

$$x_t = \alpha_0 + \alpha_1 dum_t + \varepsilon_t$$

$$\varepsilon \sim N(0,h)$$

Where ε is the error term or the unexpected component in the mispricing series and h, the variance of the error term, is a constant. Dum_t is a dummy variable that takes on the value of "0" before January 29, 1993 and "1" after that date. Thus, the mispricing is assumed to hover around the value of α_0 before January 29, 1993 and around $\alpha_0 + \alpha_1$ thereafter. The coefficient of the dummy variable, α_1, captures any structural shift that exists after the introduction of the SPDRs.

Table 3 shows the results of the OLS estimation on the mispricing series using daily prices from the nearby contracts held until expiration. In other words, for a given contract, we use prices from each trading day from the day the previous contract expires until the day that contract expires.[24] The parameter estimates indicate that there is a structural shift in the futures prices coincident with the introduction of SPDRs. Both parameter estimates are highly statistically significant. The estimate of α_0 is small and positive, indicating that there is a small positive pricing error before the introduction of SPDRs. The estimate of α_1 is negative but smaller than α_0 in absolute value, indicating that the positive pricing error was reduced after the introduction of SPDRs.

Table 3: OLS Estimates for Daily Futures Mispricing

	Coefficient	Std. Error	t statistic	P value
α_0	0.000319	0.00004555	6.994 *	0.0001
α_1	-0.000195	0.00006312	-3.090 *	0.0020

* Statistic is significant at the 1% level

In the previous analysis, positive and negative elements in the mispricing series offset each other. This may be inappropriate because the costs associated with positive and negative mispricing do not offset each other. Table 4 shows the results when we repeated the analysis using the absolute value of the pricing error. Like the parameters

[24]We also performed the analysis rolling over each of the expiring contracts to the next contact one week before the expiration date. The results are unaffected.

estimated from the signed data, the parameters estimated from the absolute values indicate a structural shift in the futures market coincident with the introduction of SPDRs. The estimate of α_0 is positive and highly significant, indicating positive pricing errors before the introduction of SPDRs. The estimate of α_1 is negative, but small relative to α_0, suggesting that there was a small reduction in mispricing upon the introduction of SPDRs.

Table 4: OLS Estimates for Daily Absolute Value of Futures Mispricing

	Coefficient	Std. Error	t statistic	P value
α_0	0.001008	0.00002993	33.662*	0.0001
α_1	-0.000063	0.00004148	-1.541	0.1235

* Statistic is significant at the 1% level

To model intraday futures mispricing, the following regression model is used

$$x_t = \alpha_0 + \alpha_1 dum_t + \alpha_2 dumo_t + \alpha_3 dumc_t + \alpha_4 dumw_t + \varepsilon_t$$

As mentioned earlier, Dum_t is a dummy variable to control for the introduction of SPDRs. $Dumo_t$ is a dummy variable that takes the value unity each time the market opens. $Dumc_t$ captures the end of the day effect by taking on the value 1 when the market closes. $Dumw_t$ controls for the weekend effect by taking the value unity on Mondays. The error term ε_t from the mispricing series is assumed to be normally distributed with a zero mean and a constant variance. Table 5 shows the parameter estimates of the above regression model.

Table 5: OLS Estimates for Intradaily Futures Mispricing

	Coefficient	Std. Error	t statistic	P value
α_0	0.000350	0.00001875	18.667*	0.0001
α_1	-0.000259	0.00002272	-11.382*	0.0001
α_2	-0.000110	0.00003258	-3.384*	0.0007
α_3	0.000000215	0.00003324	0.006	0.9949
α_4	0.000028319	0.00002908	0.974	0.3301

* Statistic is significant at the 1% level

The coefficient of the dummy variable that controls for the introduction of SPDRs is negative and significantly different from zero. This implies that futures mispricing has decreased on average. The mispricing seems to be lower on the open and higher, but not significantly, on the close and on the weekend.

The above results should be interpreted with caution. In particular, the Ljung-Box (1978) portmanteau test statistic for up to twentieth order serial correlation in the residuals from the above OLS model takes the value Q(20) = 53396 which is not insignificant at any reasonable level in the corresponding asymptotic χ^2_{20} distribution. In addition to that, the squared residuals series is clearly correlated over time, as reflected by the highly significant Ljung-Box test statistic for absence of serial correlation in the squares, $Q^2(20) = 3326$ distributed asymptotically as a χ^2_{20} distribution. This presence of serial dependence in the conditional first moments along with the dependence in the conditional second moments is one of the implications of the ARIMA and GARCH (p, q) models. Furthermore, the unconditional sample kurtosis k = 5.06 exceeds the normal value of three by several asymptotic standard errors. This is also in accordance with the implications of the GARCH(p,q) model.

the t-statistic associated with the intervention variable determines whether the introduction of SPDRs is associated with a structural change in the futures mispricing time series.

Different ARIMA specifications were tried, and it was found that the ARIMA (4,0,4) model provides the best fit for the mispricing series. The results of the ARIMA (4,0,4) model and general descriptive statistics of the daily and intradaily mispricing series are presented in Table 6 and Table 7 respectively. The coefficient of the intervention variable is negative but not significantly different from zero. This implies that after the introduction of SPDRs, the futures mispricing decreased in value but not considerably.

The Ljung-Box test statistics for the daily residuals and the intradaily residuals from the estimated ARIMA (4,04) model take the value of 16.90 and 18.36 respectively. These values are not significant at the 1% level and thus do not indicate any further first order serial dependence. The Ljung-Box statistics for the squared residuals are however, indicative of misspecification, and the very high values for $Q^2(20)$ for both the daily and intradaily mispricing series, strongly suggest the presence of conditional heteroskedasticity. Skeweness and Kurtosis are also significant indicating that a GARCH model would be appropriate. This conclusion is supported by the results of Engle Arch tests shown in Table 2.1 and Table 2.2 of the appendix.

$$Model: \quad x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{p} \phi_i x_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

Table 6: Estimates of ARIMA (4,4) Model for Daily Futures Mispricing: Jan 1990-Jun. 1996

	Coeff.	Std Error	T-Stat	P-Value
α_0	0.000308	0.000159	1.93179	0.053565
ϕ_1	0.464005	0.285375	1.62595	0.104161
ϕ_2	-0.20872	0.327571	-0.63717	0.524106
ϕ_3	-0.06407	0.317052	-0.20208	0.839877
ϕ_4	0.607604	0.241758	2.51328	0.012061
θ_1	-0.24559	0.290334	-0.84588	0.397746
θ_2	0.337086	0.273397	1.23295	0.217779
θ_3	0.189225	0.3119	0.60669	0.544147
θ_4	-0.45174	0.194197	-2.32619	0.020135
α_1	-0.00018	0.000215	-0.82855	0.407485
Log Likelihood				10003.45
Number of Observations				1584
Skeweness				0.03969
Kurtosis				9.30828
Q(20)				16.9018
$Q^2(20)$				35.2081*

* statistics is significant at the 5% level
Q(20) and $Q^2(20)$ denote the Ljung-Box (1978) portmanteau tests for up to twentieth order serial correlation in the levels and the squares respectively.

Table 7: Estimates of ARIMA (4,0,4) Model for Intradaily Futures Mispricing: Jan 1990-Jun. 1996

	Coeff.	Std Error	T-Stat	P-Value
α_0	0.0003005	0.0001495	2.01063	0.0444
ϕ_1	0.6926395	0.1724401	4.0167	0.0001
ϕ_2	0.4140275	0.2051035	2.01863	0.0436
ϕ_3	0.1590905	0.1950653	0.81558	0.4148
ϕ_4	-0.2764756	0.1210429	-2.28411	0.0224
θ_1	-0.3659653	0.173422	-2.11026	0.0349
θ_2	-0.3707546	0.1629785	-2.27487	0.0229
θ_3	-0.2277399	0.1740368	-1.30857	0.1907
θ_4	0.1101962	0.079825	1.38047	0.1675
α_1	-0.0002111	0.000198	-1.06594	0.2865
Log Likelihood				73148.475
Number of Observations				11088
Skeweness				-0.79358
Kurtosis				15.62224
Q(20)				18.3652
$Q^2(20)$				644.5493*

* Statistic is significant at the 5% level.
Q(20) and $Q^2(20)$ denote the Ljung-Box (1978) portmanteau tests for up to twentieth order serial correlation in the levels and the squares respectively.

3. Mispricing under a GARCH Model

3.1. GARCH Model

The patterns of mispricing shown in Figure 1 and Figure 3 (see appendix 6) depict a typical pattern exhibited by a series with autocorrelation and heteroskedasticity. The variance of mispricing seems to change over time and the changing variance is related to the previous level of mispricing. Such a time varying variance can be modeled using the Generalized Autoregressive conditional Heteroskedastic (GARCH) framework of Engle (1982) and Bollerslev (1987).

Standard OLS regression relies on the assumption that the variance of the dependent variable is constant over time, an assumption that fits few financial time series. Since the variance of the mispricing of S&P 500 Index futures may not be constant, a GARCH model [Engle (1982), Bollerslev (1987)] will provide a more rigorous test for a structural shift in the mispricing at the time of the introduction of SPDRs. Over the past few years, the GARCH (1,1) specification has emerged as the most frequently used alternative to OLS regression in testing for structural shifts in financial time series. The ARIMA(4,0,4) model tested above allowed to get rid of first order autocorrelation. However, as demonstrated by the Ljung-Box statistics, severe second order serial correlation still persists after fitting the ARIMA model. Thus fitting the unexpected component or the error term of the ARIMA model to a GARCH model may solve the problem.

The following expression provides the ARIMA(4,0,4)-GARCH(1,1) model for the mispricing time-series:

$$x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, h_t)$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 dumo_t + \beta_4 dumc_t + \beta_5 dumw$$

Where the first equation is the ARIMA(4,0,4) equation and is the same as the one specified in the previous section. x_t is the index futures mispricing at time t, ε_t is the error term from the ARIMA model, and h_t is the conditional variance of the error term.

The maximum likelihood approach is used to estimate the parameter coefficients, given by

$$L_t(\delta) = \sum_{t=1}^{T} \log f(\varepsilon_t | \psi_{t-1})$$

Where δ denotes all the unknown parameters in the model and T is the sample size.

The OLS model could be regarded as a special case where β_1 and β_2 are both zero. h_t is the conditional variance of the error term. As in the OLS model, Dum_t is a dummy variable that takes on the value of "0" before January 29, 1993 and "1" after that date. The coefficient of this dummy variable, α_1, captures any structural shift that arises after the introduction of the SPDRs. The other dummy variables are as specified in the OLS model. This time, these variables are included in the variance equation to capture any volatility intraday pattern. It is documented that returns volatility is high near the open and the close resulting in a U-shaped intraday pattern[25]. Several theories relate some or all of these patterns to changes in information trading across the day. These explanations of the observed patterns suggest that there are many information traders active near the

[25] See Wood, McInish, and Ord (1985), Harris (1986), Jain and Joh (1988), Neal (1988), Jordan et al. (1988), French and Roll (1986), Ekman (1992) etc...

open, and, perhaps, many liquidity traders active near the close. Other explanations should be considered. These include: (1) the patterns are sample specific, i.e., they only occur in the relatively short periods studied; (2) the patterns are caused by institutional factors, i.e., different patterns may occur in different markets; and (3) some of the patterns may be caused by the effects of non-synchronous trading on intraday indices.

3.2. GJR GARCH Model

The GJR GARCH, proposed by Glosten, Jagannathan and Runkle (1993), is a similar model except that the conditional variance equation has a somewhat different specification. As well as using the lagged squared residual, and lagged conditional variance in the conditional variance equation, the model includes a dummy variable which represents the square of the lagged residual when this residual is negative and "0" otherwise. The reason behind including the dummy variable is that volatility may be different if we have negative mispricing as opposed to positive mispricing. In fact, when prices are falling, there is a higher tendency to get negative mispricing and therefore higher volatility. This model thus captures the effect that a negative mispricing term will have on the conditional variance of the hourly index futures mispricing.

$$x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, h_t)$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 S_{t-1}^- \varepsilon_{t-1}^2 + \beta_3 h_{t-1} + \beta_4 dumo_t + \beta_5 dumc_t + \beta_6 dumw$$

Where S^-_{t-1} is a dummy variable that takes the value 1 when ε_{t-1} is negative, and 0 when

ε_{t-1} is positive. The other variables are the same as in the GARCH(1,1) model described above.

3.3. TGARCH Model

TGARCH model is another GARCH model that is used as an alternative specification. Bollerslev (1987) extends the GARCH model developed in Bollerslev (1986) to allow for conditionally t-distributed errors by specifying the conditional distribution of the errors to be a transformed inverted gamma-1 distribution. Bollerslev's development permits a distinction between conditional heteroskedasticity and a conditional leptokurtic distribution, either of which could account for the observed unconditional kurtosis in the data.

$$x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$
$$\varepsilon_t | \psi_{t-1} \sim f_d(\varepsilon_t | \psi_{t-1})$$
$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 dumo_t + \beta_4 dumc_t + \beta_5 dumw$$

The loglikelihood function for the TGARCH model is similar to the one for a simple GARCH model but it includes an additional parameter for the degrees of freedom.

$$L_T(\delta) = \sum_{t=1}^{T} \log f_d(\varepsilon_t | \psi_{t-1})$$

Where δ denotes all the unknown parameters in the model, d is the degree of freedom parameter, and T is the sample size.

The idea behind using a GARCH model is to relax the assumption of a constant variance that is encountered in OLS or ARIMA models. According to ARCH and GARCH models the conditional error distribution is normal, but with conditional variance equal to a linear function of past squared errors and past conditional variances. Thus, there is a tendency for extreme values to be followed by other extreme values, but of unpredictable sign; a behavior that is observed in most financial time series. In addition to the ability of modeling volatility, the GJR-GARCH model investigates leverage effects on the volatility of the time series by examining the effect of negative error terms on the conditional variance. Despite the advantages of GARCH models, it is not clear whether these models sufficiently account for observed fat-tailed distribution of certain financial time series. The T-GARCH model presented in the previous section with conditionally t-distributed errors may have a greater descriptive validity. Thus, these three GARCH models will permit to evaluate different aspects of the index futures mispricing series.

For all the GARCH models described above, the mispricing is assumed to hover around the value of α_0 before the introduction of SPDRs, and around the value of α_0 plus α_1 after January 29, 1993. The coefficient of the dummy variable thus captures any structural shift that arises after SPDRs are introduced.

4. Results of Garch Models

The various sign tests described by GJR and by Engle and Ng (1993)[26] were used to check the specification of the various models. The results of the different sign tests run on the daily and intradaily mispricing models (Appendix 1: Table 3.1 and 3.2 respectively) were in favor of the ARIMA(4,0,4)-TGARCH(1,1) for both the daily and the intradaily mispricing series. None of these tests are significant, meaning that the conditional variance equation of the model does not seem to require a further parameter representing the direction of the error term. The same conclusion is reached when comparing the models according to the Ljung-Box Portmanteau test. A summary of the Q and Q^2 statistics of the various mispricing models discussed in this paper is provided in Table 4.1 and 4.2 of the appendix. Maximum Likelihood estimates of the parameters of the ARIMA(4,0,4)-TGARCH(1,1) model are presented in Table 8 and Table 9[27] along with asymptotic standard errors. The estimates are obtained by the BHHH (Berndt, Hall, Hall and Hausman (1974)) algorithm.

Tables 8 and 9 demonstrate that using the ARIMA(4,0,4)-TGARCH(1,1) model, rather than the ARIMA(4,0,4) model, has an effect upon our results for both the daily data and the intradaily series. As mentioned before, the error terms of the ARIMA(4,0,4) model do not exhibit any first order serial correlation. However, second order serial dependence was substantial. This absence of first order serial dependence along with the second order serial independence is one of the implications of a GARCH model. The

[26] A definition for the sign tests is included in the appendix.

Ljung-Box test statistic for the daily (intradaily) standardized residuals and the standardized squared residuals from the estimated ARIMA(4,0,4)-TGARCH(1,1) model take the values Q(20) = 17.15 (0.71) and $Q^2(20)$ = 5.66 (0.001), respectively, which are not significant at the 5% level, and thus do not indicate any further first or second order serial dependence in neither the daily nor the intradaily series.

In Table 8 we show the results of the ARIMA(4,0,4)-TGARCH(1,1) estimation on the daily-signed data from the mispricing series. The size, sign, and significance level of the α_0 and α_1 terms are consistent with those shown in Table 6. The estimate of α_0 is significantly positive, once again indicating that there is a small positive pricing error before the introduction of SPDRs. The estimate of α_1 is negative but not significantly different from zero. It is also smaller than the estimate of α_0 in absolute value, indicating that the positive pricing error was reduced but not significantly after the introduction of SPDRs. Both the estimate for the coefficient of the square of the previous error term (β_1) and the estimate for the coefficient of the previous variance term (β_2) are highly significant.

[27] Results of the other tested models fitted to daily and intradaily series are included in Appendix 2 and Appendix 3 respectively. Results for rolled over contracts are in Appendix 4 and Appendix 5.

$$Model: \quad x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}$$

Table 8: Estimates of ARIMA(4,4)-TGARCH(1,1) Model for Daily Futures Mispricing: Jan. 1990-Jun 1996)

Variable	Coefficient	Std Error	T-Stat	P-Value
α_0	7.25E-05	3.51E-05	2.06488*	0.0389
ϕ_1	0.425	0.13	3.27855*	0.0010
ϕ_2	-8.19E-02	0.163	-0.50373	0.6145
ϕ_3	-0.285	0.151	-1.88828	0.0590
ϕ_4	0.733	0.107	6. 84263*	0.0000
θ_1	-0.174	0.138	-1.26394	0.2063
θ_2	0.234	0.145	1.60938	0.1075
θ_3	0.409	0.147	2.78371*	0.0054
θ_4	-0.497	8.82E-02	-5.63672*	0.0000
α_1	-1.71E-05	4.37E-05	-0.38973	0.6967
β_0	1.78E-08	7.71E-09	2.31564*	0.0206
β_1	3.07E-02	9.03E-03	3.39893*	0.0007
β_2	0.952	1.37E-02	69.39854*	0.0000
d^a	5.776	0.661	8.73946*	0.0000

Log Likelihood	19903
Number of Observations	1584
Skeweness	-1.01451
Kurtosis	16.48864
Q(20)	17.1569
$Q^2(20)$	5.6645

* Statistic is significant at the 5% level.
a d is the degree of freedom parameter in the loglikelihood function.
Q(20) and $Q^2(20)$ denote the Ljung-Box (1978) portmanteau tests for up to twentieth order serial correlation in the levels and the squares respectively.

In Table 9 we provide the results of the ARIMA(4,0,4)-TGARCH(1,1) estimation on the intradaily mispricing series. The size, sign, and significance level of the α_0 and α_1 terms are similar to those generated by the ARIMA(4,0,4) analysis (Table 7). Once again, the estimate of α_0 indicates positive pricing errors before the introduction of SPDRs. The negative estimate of α_1, which is almost equal to the estimate of α_0 in absolute value, indicates that there was a significant reduction in mispricing upon the introduction of SPDRs. The estimated coefficient for the square of the previous error term (β_1) and the estimated coefficient for the previous variance term are both highly significant.

$$Model: \quad x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 dumo_t + \beta_4 dumc_t + \beta_5 dumw$$

Table 9: Estimates of ARIMA(4,4)-TGARCH(1,1) Model for Intradaily Futures Mispricing: Jan. 1990-Jun 1996

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	5.41E-04	9.63E-05	5.61812*	0.0000
ϕ_1	-2.92E-02	0.152	-0.19208	0.8477
ϕ_2	8.86E-02	2.35E-02	3.76612*	0.0002
ϕ_3	0.959	1.74E-02	55.25633*	0.0000
ϕ_4	-8.84E-02	0.149	-0.59393	0.5526
θ_1	0.228	0.162	1.41073	0.1583
θ_2	8.72E-02	5.01E-02	1.74099	0.0817
θ_3	-0.759	2.57E-02	-29.51536*	0.0000
θ_4	3.87E-02	0.126	0.30833	0.7578
α_1	-5.15E-04	1.27E-04	-4.05546*	0.0001
β_0	-5.63E-09	3.06E-09	-1.83675	0.0662
β_1	-1.87E-02	1.37E-03	-13.63261*	0.0000
β_2	0.753	6.99E-03	107.65707*	0.0000
β_3	2.45E-06	2.20E-07	11.12833*	0.0000
β_4	2.59E-06	2.54E-07	10.18651*	0.0000
β_5	1.32E-06	1.42E-07	9.26919*	0.0000
d^a	8.104	0.918	8.82604*	0.0000

Log Likelihood	61516.701
Number of Observations	11088
Skeweness	-0.93991
Kurtosis	10.12769
Q(20)	0.7085
$Q^2(20)$	1.7377e-003

* Statistic is significant at the 5% level.
a d is the degree of freedom parameter in the loglikelihood function.
Q(20) and $Q^2(20)$ denote the Ljung-Box (1978) portmanteau tests for up to twentieth order serial correlation in the levels and the squares respectively.

In this model, in addition to the lagged conditional variance, and the lagged squared unexpected component of the intradaily futures mispricing, the conditional variance equation includes three dummy variables: $dumo_t$, $dumc_t$, and $dumw_t$. These variables are included to see if there is any intraday pattern in the mispricing volatility. The estimated coefficients of these variables are all positive and significantly different from zero. This implies that the volatility of the mispricing series is high near the open and the close and also on Mondays indicating the presence of the familiar U-shaped intraday pattern.

SUMMARY

This section examines the effect of SPDRs' trading on the pricing efficiency of the S&P Index futures contracts. Easy availability of a security that tracks the movement of a stock index can contribute to increased activity and market efficiency of other index related products. But if such a security provides a better substitute for other index products in tracking general market co-movement, these other index products will show reduced activity and market efficiency. One attribute of efficiency in the S&P 500 Index futures markets is mispricing which is tested to observe any change after the introduction of SPDRs.

When the measure of efficiency is based on the daily signed difference between the observed futures price and the theoretical futures price, we find a very small, but statistically significant positive pricing error before the introduction of SPDRs, which is eliminated or reversed when SPDRs are introduced. However, signed differences may not accurately reflect the costs associated with mispricing. When the absolute value of the daily differences are used, the results unambiguously show an improvement in the pricing efficiency of the futures markets upon the introduction of SPDRs. Using the ARIMA (4,04) with an intervention variable and the ARIMA(4,0,4)-TGARCH(1,1) models, rather than the OLS model, has very little effect upon our results for either the daily signed data or the absolute values, even when the estimated coefficients for the square of the previous error terms and the previous variance terms are statistically significant.

The analysis was extended using intraday price data for the futures contract and the S&P 500 Index. When using the OLS model, the intradaily mispricing results were similar to those of the daily results. However, the ARIMA(4,0,4) and the ARIMA(4,0,4)-TGARCH(1,1) models added a substantial improvement to the analysis. The ARIMA(4,0,4) model solves the problem of first order serial correlation in the intradaily futures mispricing series. The unexpected component of the mispricing series, after fitting the ARIMA(4,0,4) model, is approximately uncorrelated over time but characterized by tranquil and volatile periods. The standardized t-distribution fails to take account of this temporal dependence, and the GARCH models with conditionally normal errors do not seem to fully capture the leptokurtosis. Instead, the TGARCH(1,1) model fits the data series quite well. Estimates based on this model prove that deviations from theoretical prices are much smaller after the introduction of SPDRs. The positive mispricing is reduced and almost eliminated in the second half of the testing period that is after January 29, 1993. This means that the S&P 500 index futures prices are more in compliance with their theoretical values and that the performance of the index futures market seems to have improved with SPDRs.

Since GARCH models permit for the variance to be non-constant, we took the opportunity to investigate whether previously observed intraday patterns are present in the

S&P 500 index futures mispricing series. Three dummy variables were included in the conditional variance equation to capture the open effect, the close effect, and the weekend effect. The estimated coefficients of these three dummy variables were positive and significantly different from zero. The results refer to the famous volatility U-shaped intraday pattern where the volatility is high near the open and the close. One possible explanation for these patterns is that both the S&P 500 stock index and the S&P 500 index futures exhibit similar volatility patterns[28].

[28]Ekman (1992), "Intraday Patterns in the S&P 500 Index Futures Market", Journal of Futures Markets, Vol. 12, No. 4, p. 365-381

STANDARD AND POOR'S DEPOSITORY RECEIPTS AND THE PERFORMANCE OF THE S&P 500 INDEX OPTIONS MARKET

INDEX OPTIONS:

1. An Overview of Index Option Contracts:

Index options began trading in the United States on March 11, 1983. The first was the CBOE 100 and was later renamed the S&P 100. It is now frequently called the OEX. By the end of 1983, options on different indices traded not only on the CBOE, but also on the American, Philadelphia, and New York Stock Exchanges.

An index option is a contract that transfers equity market risk from the buyer to the seller. The option buyer is willing to pay a price – known as the premium – for the right to benefit from an increase or a decrease in the value of the underlying index with the risk of limited loss to the premium paid. The seller of an index option is willing to grant that right and accepts the risk of market variability in return for this premium. Each CBOE index option contract represents $100 (the index multiplier) times the current value of the index. For example, when the index is at 550, the underlying dollar value of 1 index option contract is equal to $55,000. An index call gives the holder of the option the right, but not the obligation, to buy $100 times the index value at a predetermined price –

known as the exercise price. The value of an index call option at expiration, or upon exercise, is the amount by which the settlement value of the index exceeds the strike (exercise) price times the index multiplier. The settlement value may be based on either the closing of the primary market for the underlying securities in the index or, in some cases, the opening of all the component securities. The value of an index put option at expiration, or upon exercise, is the amount by which the value of the index is below the strike price. The option contract requires cash settlement so that a writer, on being assigned an exercise of a call, delivers in cash the difference between the index value and exercise price.

Index options offer investors an efficient way to speculate on the future direction of the stock market and a way to effectively buy the market today at a low cost. This is particularly advantageous for investors with low cash positions but wishing to bet on the direction of the market. Index options can also be used to hedge an existing portfolio against a systematic decline in equity value.

Amongst the most heavily traded index option contracts are the S&P 500 index contracts. These options are European in nature[29]. There are actually three types of contracts: the SPX, SPL, and NSX contracts. SPX, the Standard & Poor's 500 Index Option continues to be the world's leading exchange-traded European-style index option. Since its introduction in 1983, SPX option volume has grown to reach an average daily contract volume of more than 105,000 in 1995. CBOE's options on the S&P 500 index posted the second highest volume year ever in 1995 with 26,726,023 contracts. The SPX contract has up to six expiration months available for trading: the two nearby months and as many as four months from the March-June-September-December cycle. The expiration date is usually the Saturday immediately following the third Friday of the expiration month. Trading in SPX options will ordinarily cease on the business day (usually Thursday) preceding the day on which the exercise settlement value is calculated. SPX options generally may be exercised only on the last business day before expiration. The settlement value is calculated using the opening reported sales price in the primary market of each component stock on the last business day (usually a Friday) before the expiration date. If a stock in the index does not open on the day on which the settlement value is determined, the last reported sales price in the primary market will be used instead. The SPL contract has expiration months in June and December, up to two years in the future providing investors, particularly institutional investors, with longer-term options on the market. The NSX option was introduced in order to allow investors to escape the price volatility caused by "triple witching days". For SPX and SPL contracts, the final settlement price is based on the closing prices of the underlying stocks on the third Friday of the expiration month. In contrast, the NSX final settlement price is based on the opening prices of the index component stocks on the third Friday of the delivery month. Other index options introduced by CBOE include the OEX LEAPS (Long Term Equity Anticipation Securities) and SPX LEAPS. These have the same properties like the regular SPX except that they have times to maturity as long as three years.

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[29] Before April 1986, S&P 500 options were American options.

2. *Difference Between Index Options and Stock Option Contracts:*

There are important discrepancies between index options and stock options which may give rise to possible changes in option pricing and strategy between the two forms of contracts and lead to greater mispricing potential in index options. The four main differences are: (1) the underlying asset for the index option is a portfolio rather than a single common stock; (2) index options are cash settled (3) the dividend stream on the index is more complex than that on a common stock; and (4) the distribution of the underlying index might not be approximated by the lognormal:

1. Underlying Asset is a Portfolio: Hedging with stock option contracts is both easy and very straightforward. This is not the case with index options, since the underlying security is a portfolio, i.e. the index, and an investor who wishes to arbitrage between the option and the underlying assets has to follow more complicated procedures. This is particularly true with the S&P 500: to create a riskless hedge, an investor needs to accumulate the proper number of shares of each of the 500 stocks at the existing spot price. In practice, however, it is almost impossible to construct a portfolio that exactly reproduces the index. Since there is no simple arbitrage between the option and the underlying index, as there is with stock options and their underlying assets, it is conceivable that arbitrage forces are not as powerful with index options and hence index options may display greater pricing errors than do stock options.
2. Cash Settlement: Another major difference between index options and stock options is that index contracts are cash settled. Since it would be quite difficult and costly to accumulate each of several hundred stocks in their proper weights in order to

make or take delivery, index options do not permit the delivery of the underlying asset. Instead, on the exercise of an index call, the assigned writer is obligated to pay the exercising holder cash equal to the difference between the closing level of the index on the exercise date and the exercise price. Thus, when an investor exercises an option, the exact amount of cash that will be received is only known after the market has closed.

3. Dividend Stream on the Index: It is now widely known that the dividend payments on stocks have a major impact in the pricing of stock options (Merton 1973). The dividend stream for index options is more difficult to predict than that of an individual stock. This has offsetting impacts: first, there is much more research required in estimating an accurate dividend stream for index options. However, the resultant dividend stream looks more continuous than that of a stock option. This problem is not too serious when dealing with European style options such as those on the S&P 500 index (SPX, SPL, NSX) since one need not worry about possible early exercise.

4. Distribution of index returns: Most of the theoretical pricing formulas for options rely upon the fact that the return distribution of the underlying asset is lognormal with constant variance. For individual stocks this assumption may be quite reasonable. However, this is not necessarily the case for an index. The latter is more likely to show significant non-stationarity in return.

The actual impact of these issues on the mispricing of options on indices is an empirical question on which we shall attempt to shed some new light in this study.

LITERATURE REVIEW

The original Put-Call Parity model was developed by Stoll (1969) and later extended and modified by Merton (1973). Both models were empirically tested by Stoll (1969) and Gould and Galai (1974) for over the counter put and call options. While these studies basically supported the Put-Call Parity theory, some inefficiencies in the relationship were also found to exist. Gould and Galai (1974), however, find that the basic model is not supported unless rather large transaction costs are included. In fact, these costs were found to wipe out any exploitable profit opportunities in the OTC options market for the 1967-1969 period.

Galai (1978) examines daily closing prices of the CBOE during the exchange's first 6 months of operation. Two hypotheses are formulated. The first hypothesis argues that the stock and options markets are well synchronised so that simultaneous closing prices are within their theoretical boundaries. Results of the ex post test are inconsistent with this hypothesis especially for options with short maturity. The second hypothesis claims the market is efficient. Ex ante tests indicate that, on average, positive profits could have been exploited especially for deep in the money options with a short time to maturity, but the returns per transaction could not be expected to be non-negative. The frequent deviations could neither be explained by the assumption of perfect knowledge of the future dividends nor by the possible inaccuracy of the data.

Klemkosky and Resnick (1979) have extended the theoretical Put-Call Parity models developed by Stoll (1969) and Merton (1973) by including a dividend term and assuming that neither the call nor the put would be exercised early and that future dividends are known with certainty. Utilising CBOE American options for the period of July 1977 to June 1978, the empirical results are consistent with Put-Call Parity theory. The study also shows that many reverse conversions[30] appear to be conditionally profitable at initiation. Whether this profit will be realised is uncertain and dependent upon the premature exercise of the put. The reported $20 profitability level is not an adequate compensation given that the arbitrageur now operates in markets where the options are not dividend-payout protected and that option prices and stock prices change continuously. Klemkosky and Resnick (1980) tested the profitability of those hedges in an ex-ante manner using the ex post results as a signal to trigger investment decisions. The long hedge results indicate an overall tendency for ex ante profitability to be less than ex post profitability and for price corrections to take place rapidly enough to eliminate most if not all of the possible arbitrage profits. Those profits are sensitive to the level of transaction costs and are unlikely even for member firms. Returns on long hedges are positive on average even after considering transaction costs and higher than the returns on the short hedge investments. This is expected as long hedges are riskless while short conversions are risky because of the possibility of premature termination of the position.

Using bid-ask prices of options traded on the CBOE for the period August 1976 to June, 1977, Bhattacharya (1983) performs lower boundary conditions tests based on the

[30] A reverse conversion or a short hedge can be set up by writing a put, shorting the stock, buying a call, and lending an amount equal to the present value of the exercise price at the risk free rate.

rational pricing of call options and an implied standard deviation test. He finds small and infrequent violations of the boundary conditions. However, the returns resulting from the executed hedges are on average positive only when transaction costs are ignored. Frequent violations of the tighter boundary conditions in the implied standard deviation test are reported but the estimated profits cannot be unambiguously attributed to option market inefficiency.

Using TSE option and stock transaction data for the period 1978-1979, Halpern and Turnbull (1985) investigate (1) the conformance of observed prices to various boundary conditions without accounting for the bid-ask spread, (2) the evolution of the market over time, and (3) the efficiency of the market. They find that violations did occur but rarely when the option is out of the money. They observe almost no relationship between the number of days to maturity on the option and the number of violations. However, when considering the average size of the violation, they show that: (i) there tends to be a positive relationship between the number of days left to maturity and the average dollar size of the violation; (ii) the size of the violation tends to be greater for deep in the money options than for in the money options; and (iii) the average size of the violation tends to increase with the number of dividends expected to be paid before the exercise date. When looking at the nature of the market over time, two hypotheses are considered. The first examines whether the probability of observing a violation changed over time. The second hypothesis concerns the magnitude of the violations. They demonstrate that both the frequency and the magnitude of violations tend to increase rather than decrease. To test for market efficiency, they use the occurrence of a violation as a signal to implement a trading rule. It is found that the arbitrage mean dollar returns are positive and statistically different from zero. These results strongly suggest that the TSE option market over the sample period was inefficient. The authors note that the sample period exhibited substantial growth in interest in the option market, and argue that the above results should be treated with caution and should not be generalised to periods where the market has matured and its growth has levelled off.

Evnine and Rudd (1985) examine the pricing of the options on the S&P 100 and the Major Markets Index using intradaily prices from June till August 1984. Their findings suggest that American index options on the S&P 100 and the MMI were both overpriced and underpriced relative to both European and American PCP. The overpricing is found to be a reflection of the early exercise feature. As for the underpricing, it is suggested that it might reflect non-synchronous data. Evnine and Rudd also observe substantial deviations between market prices and theoretical prices derived from the binomial option-pricing model. They suggest that tests of option pricing models might be more difficult than was previously realised due to non-synchronous prices. They conclude that the market is inefficient to some degree and that much of this inefficiency might be explained by the inability of investors to arbitrage the index options at low risk.

Chance (1987) tests Put-Call Parity for index options using a data base of bid and ask prices of S&P 100 index options for the first four months of 1984. He observes frequent violations that represent a potential source of abnormal returns for index options traders. However, he suggests that when accounting for dividend reinvestment (financing) by buying (selling short) additional shares of the index, the subsequent transaction costs would almost surely exceed the potential returns. Chance also provides another way of testing for parity: the box spread strategy[31]. He finds that index option prices are consistent with the box spread rule. According to Chance, this consistency is due to the fact that the necessary arbitrage cannot be executed at sufficiently low cost to support the parity rule, so index option traders, by necessity, choose spreads and straddles as their predominant transactions. Chance (1988) uses the same database again to determine whether the prices at which trades can be executed adhere to rational boundary conditions. The relationship between pairs of options is also examined through the vertical spread test[32] and the butterfly spread test[33]. Only a small number of violations is reported. Chance concludes that index options are priced consistently with rational boundary conditions.

Using data from the Finnish Options Index (FOX), Puttonen (1993) tests the rational lower boundary conditions for call options as well as put options as determined by the futures price instead of the index price. The study also provides a comprehensive analysis of the relevant transaction costs related to the boundary conditions. Only one violation of the put lower boundary is found, and several violations of the call lower

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[31] Box Spread: Long position in a call with low exercise price (X_1) and a put with high exercise price (X_2), short positions in a call with high exercise price (X_2) and a put with low exercise price (X_1), and a short position in risk free bonds having face value (X_2-X_1).

[32] Vertical spread test: one call with low exercise price X_1 is sold at C_{1b}, one call with high exercise price X_2 is bought at C_{2a} and bonds having face value (X_2-X_1) are bought. Cash flows at expiration are non-negative implying that the portfolio requires a positive cash outflow, that is: $-C_{1b} + C_{2a} + (X_2-X_1)\, e^{-rt} \geq 0$

[33] Butterfly spread test: Three options with exercise prices $X_1<X_2<X_3$. A portfolio is constructed consisting of a long position in a units of the call priced at C_{1a} and (1-a) units in the call priced at C_{3a}, and a short position in one unit of the call priced at C_{2b} where $a = (X_3-X_2)/(X_3-X_1)$. The portfolio has non-negative cash flows at expiration so it must have a negative initial cash flow. Therefore:

$aC_{1a} - C_{2b} + (1-a)C_{3a} \geq 0$

boundary are observed for deep in the money and at the money categories. The results are consistent with Halpern and Turnbull (1985), except that violations on the FOX market are of greater magnitude.

Kamara and Miller (1995) perform Put-Call Parity tests on S&P 500 index options using daily data from May 1986 to May 1989 and intradaily data for the first three months of 1989. The study documents some deviations from PCP during 1986 to 1989 with less frequent and smaller deviations in 1989 than in earlier years. The deviations are also less frequent and smaller than those found in earlier PCP studies using American options. The results suggest that the trading strategies underlying PCP are subject to significant liquidity (or, immediacy) risk of adverse price movements from order submission until order execution. Kamara and Miller (1995) find a systematic relation between those deviations and proxies for liquidity risk in the stock and option markets. As liquidity risk increases, the frequency and size of the deviations increase. In other words, the bid prices of call and put options rise relative to their PCP implied bid prices and the ask prices of call and put options fall relative to their PCP implied ask price. When investigating PCP violations in intraday transaction data, it is found that almost half of these arbitrage opportunities result in a loss when execution delays are assumed to be equal to the median time between option quote update.

Figlewski (1988) examines call options on the NYSE Composite index from September 1983 to September 1984 using the Black-Scholes option valuation model. He finds that the model captures the major portion of option price determination in the market place. However, not all encountered arbitrage opportunities are eliminated. When the sample is broken down according to "moneyness", Figlewski finds that out of the money options were relatively more overpriced than those at or in the money options. There is a better fit to the model for options with longer time to expiration, and for sub-samples in the later period than in the first period. Along the lines of Brenner, Courtadon, and Subrahmanyam (1987), Figlewski proposes the possibility that stock index options may not be priced off the spot index value, but rather off the futures price. Thus, he investigates the alternative of taking an offsetting position not in the cash index but in the index futures. Option prices are found to be closer, on average, to model values based on the actual cash index than to model values based on "implied cash index" derived from the futures price. However, regressions including both model values as explanatory variables showed that the futures market had a markedly greater influence on the price behaviour of the NYSE call options. It is also noted that the closer the match expirations of the option and the futures contract, the larger was the relative influence of the futures based model value on the market place.

Cotner and Horrell (1989) evaluate the Black-Scholes option-pricing model with respect to the pricing of call options on the S&P 100 index for the period March 1983 through December 1985. The mean pricing errors from the tested model are relatively small and decline greatiy as the options approach maturity. The average size of the errors using the implied variance (instead of historical variance) is much smaller at all days to maturity. The results are also remarkably similar to those of Evnine and Rudd (1985) who used closing prices for their study. The analysis reveals that the level of the risk free rate of interest, the time to maturity, the level of the index return estimate, the type of variance estimate, and the degree to which the option is out or in the money, all have statistically significant effects on the level of the mean pricing errors.

Most valuation models predict that option prices should increase monotonically with the variability of the underlying asset. It is therefore not surprising that much empirical work has been aimed at testing the efficiency of the option market and models of option pricing by comparing the historical variability of the underlying asset with the variability implicit in option prices. Barone-Adesi and Morck (1991) test whether option prices predict ex-post variability efficiently and the rational expectation of investors using S&P 100 options for the sample period of December 1983 to December 1988. Their results suggest good predictions of index variability over the remaining life of the option before the 1987 stock market crash. No reliable conclusions could be made for after the crash; option prices have not yet recovered their power of predicting future index volatility.

In general equilibrium, the volatility of the index is expected to be negatively related to the rate of interest. Consequently, it is not possible to consider the effect of stochastic volatility on index option prices without at the same time allowing the interest rate to vary stochastically. Bailey and Stulz (1989) investigate the pricing of stock index options in a general equilibrium model by allowing the interest rate and the volatility of the index to change randomly over time and to be related to each other. They show that in some cases, the sign of the Black-Scholes bias depends on whether the link between index volatility and interest rates is taken into account. They also find that, for one model of interest rate dynamics, the index option prices in their model are higher than Black-Scholes prices for deep in the money options when the interest rates are negatively related to the level of the index and lower otherwise.

Rindell (1995) test the Amin and Jarrow (1992) version of Merton's (1973) stochastic interest rate option pricing formula for stock options. In their model, the interest rate dynamics are given by the Heath et al. (1992) term structure model. The empirical results, using data on European stock index options from the Swedish option market covering a time period from January 2nd to December 30th 1992, show that the Amin and Jarrow model clearly outperforms the Black-Scholes model. Furthermore, the time to maturity bias, found in tests of the Black-Scholes model, disappears when the options are priced with the Amin and Jarrow model.

Using transaction data on the S&P 100 index options, Harvey and Whaley (1991) study the effect of valuation simplifications that are commonplace in previous research on the time series properties of implied market volatility. More particularly, previous research generally assumes that the S&P 100 index option is European-style. This option is actually American-style. It is also commonly to assume that the dividend yield is constant. In his study, the dividends are not constant and exhibit distinct seasonal patterns. Their results show that large pricing errors can be induced in the option prices if the American feature and the discrete dividends are ignored. Moreover, these option pricing errors also translate into errors in the implied volatility estimates. Harvey and

Whaley (1991) find that spurious negative serial correlation in implied volatility changes is induced by non-simultaneously observing the option price and the index level and by a bid/ask price effect if a single option is used to estimate implied volatility.

Manaster and Rendleman (1982), Bhattacharya (1987), and Stephan and Whaley (1990) provide empirical evidence relating asset prices inferred from risk-neutral option valuation models to future asset prices. The first two studies find that option prices lead stock prices. Stephan and Whaley (1990), on the other hand, conclude the opposite. One possible explanation for the conflicting results obtained in these studies is the problem of volatility estimation. Finuance (1991) uses a different approach that does not require the specification of an option pricing model or the estimation of the volatility of the underlying asset. He derives a measure of relative prices from the put-call parity for index options and applies it to a three-year sample of OEX option transactions. His study examines the hypothesis that in the presence of market friction, relative put and call prices contain information concerning future returns of the underlying asset. The results provide support for the notion that option prices can contain information concerning expected returns. The tests indicate that the measure of deviation from put-call parity leads returns on the S&P 100 by at least 15 minutes. However, a trading strategy based upon the signal of the deviation does not provide returns that are large enough to compensate for the transaction costs that would be incurred in trading the S&P 100 basket.

In short, the conclusions of most of the empirical studied mentioned above, are best summarised by noting that while most of the tested option pricing models hold, on average, violations are frequent and substantial. One problem in interpreting these results is that most previous studies that, for instance, test the Put-Call Parity using American options. As Merton (1973) shows, PCP need not hold for American options because the possibility of early exercise cannot be completely ruled out when the portfolio is established. Thus, it is not possible to conclude whether those violations are a result of market inefficiency or a failure to fully account for early exercise. Another possible explanation for those reported violations, is that the existing market imperfections such as the transaction costs and the bid/ask spread may wipe out any possible arbitrage profits when included in the analysis.

VALUATION OF INDEX OPTIONS:

Using simple dominance arguments[34], Merton (1973), Smith (1976), and Galai (1978) demonstrate that under very general conditions, the price of a call option must lie within certain upper and lower bounds. Observations, whereby the market price of an option did not conform to these bounds, would indicate the possible existence of arbitrage opportunities. The appeal of this principle is that it only requires a few rational agents who stand ready to eliminate any arbitrage opportunity. The Put-Call Parity condition (PCP) formalised by Stoll (1969) uses the no-arbitrage principle to price put (call) options relative to call (put) options. Many empirical studies that test the PCP ignore the possibility of early exercise when the portfolio is established. While some of these studies attempt to reduce the effects of possible early exercise on their tests, they have not been able to fully account for the effect of early exercise. This problem is avoided in this study by simply testing European options on the S&P 500 stock index traded on the Chicago Board Options Exchange.

The value of a call option at any time, as explained by Merton (1973), is a function of the price of the underlying asset (S), the exercise price of the option (X), the time to maturity (T), the risk free rate of interest (r), and the variance of the return on the underlying asset (σ^2). Based on these factors, a continuous time option pricing formula has been derived by Black and Scholes (1973). Using the same factors, a binomial model was later derived independently by Cox, Ross and Rubinstein (1979) and Rendleman and Barter (1979). For the purpose of this study, we will just focus on the Put-Call Parity relationship.

The theoretical framework for the arbitrage strategies is first developed. Specifically, SPX call and put options with the same exercise price and S&P 500 index are employed to establish an arbitrage position that yields a zero net cash flow position at expiration. Since SPX options are European options, early exercise is not of any concern in this study's framework. To prevent arbitrage profits, the arbitrage position should produce a non-positive initial net cash flow. The strategies employed in this study initially assume two conditions: (1) there are no transaction costs and (2) the borrowing and the lending rates are equal.

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[34] Existence of a dominant asset means that with a zero investment position, one can derive non-negative (not necessarily constant) returns under all states of the world.

The relationship between puts, calls, and the underlying asset is described by the well-known Put-Call Parity model,

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

Where C is the call price, P is the put price, S is the stock price, X is the exercise price, r is the risk-free rate, and T is the time to expiration. Equation (1) holds for European options but not for American options due to the possibility of their early exercise, especially for dividend paying stocks[35]. If the stock pays dividends, for instance at time t_1, then equation (1) becomes

$$C = P + S - X\,e^{-rT} - d\,e^{-rt1} \tag{1a}$$

If dividends are paid continuously but at a constant yield D, then equation (1) becomes

$$C = P + S\,e^{-DT} - X\,e^{-Rt} \tag{1b}$$

In dealing with index options the dividend structure of the underlying asset would seem more appropriately specified as being a continuous yield. Letting I be the current level of the index and D its dividend yield, the capital value of the index is $I\,e^{-DT}$.

As Phillips and Smith (1980) and Baesel, Shows, and Thorp (1983) note, a significant transaction cost of option trading is the bid-ask spread. Since the database in this study contains bid and ask prices, it is appropriate to derive the put-call parity formula under the assumption that trades must be conducted with market makers.

Put-Call Parity requires that the underlying instrument, in this case the index, is a marketable asset. In order to empirically test the Put-Call Parity, it is assumed that the index can be freely purchased and sold short at the current index level. This assumption

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[35] See Merton (1973), "The Relationship Between Put and Call Option Prices: Comment"

denies the fact that constructing the index would be costly and that bid and ask prices on the individual component stocks would have to be considered.

Two types of portfolios will be constructed. The first is referred to as portfolio A and consists of a long position in e^{DT} calls, a short position in e^{DT} puts, a short position in the index, and a long position in risk-free bonds having a face value of $X\, e^{DT}$. Let C_a and C_b be the ask and bid prices of the call and P_a and P_b the ask and bid prices of the put. The upper half of Table A illustrates the payoffs from this portfolio.

It is assumed that as dividends are paid on the short index, the investor sells short additional shares and uses the proceeds to pay the dividends. At expiration, the investor will have accumulated short positions in the index at a rate D. The portfolio has a zero net cash flow at expiration; thus, its current cash flow must be non-positive. Otherwise, the portfolio would have a positive cash inflow up front with no outflow at expiration. That is

$I - Xe^{DT}e^{-rT} - e^{DT}(C_a - P_b) \leq 0$ or

$$C_a - P_b + X\, e^{-rT} - I\, e^{-DT} \geq 0 \tag{2}$$

Portfolio B consists of long position in the index and e^{DT} puts, and short positions in e^{DT} calls and risk free bonds having a face value of Xe^{DT}. As dividends are received from the stocks in the index, they are used to purchase additional shares of the index. The number of shares will accumulate at a rate D. This portfolio has a zero cash flow at expiration; therefore, its current value must be negative. Otherwise, a positive cash flow will occur up front with no obligation at expiration. That is, $I - Xe^{DT}e^{-rT} + e^{DT}(P_a - C_b) \leq 0$, therefore

$$P_a - C_b - X\, e^{-rT} + I\, e^{-DT} \geq 0 \tag{3}$$

The lower part of Table A illustrates the payoffs from portfolio B.

Table A. Put-Call Parity for Index Options

		Cash Flow at Expiration	
Portfolio A	**Current Cash Flow**	$I_T \leq X$	$I_T > X$
Short index	$+ I$	$- I_T e^{DT}$	$- I_T e^{DT}$
Buy bonds	$- Xe^{DT}e^{-rT}$	Xe^{DT}	Xe^{DT}
Buy call	$- e^{DT}C_a$	0	$e^{DT}(I_T - X)$
Sell put	$+ e^{DT}P_b$	$-e^{DT}(X-I_T)$	0
Total	≤ 0	**0**	**0**

		Cash Flow at Expiration	
Portfolio B	**Current Cash Flow**	$I_T \leq X$	$I_T > X$
Buy index	$- I$	$I_T e^{DT}$	$I_T e^{DT}$
Sell bonds	$+ Xe^{DT}e^{-rT}$	$- Xe^{DT}$	$- Xe^{DT}$
Sell call	$+ e^{DT}C_a$	0	$- e^{DT}(I_T - X)$
Buy put	$- e^{DT}P_b$	$e^{DT}(X-I_T)$	0
Total	≤ 0	**0**	**0**

The basic lower pricing condition for call options is that the call ask price should be nonnegative and no less than the underlying index price; i.e., $C_a \geq I - X$, where C_a is the call ask price at time t. In theory, if this boundary condition is violated, purchasing the call and selling the index could result in arbitrage profits. However, the act of selling the index requires the simultaneous short selling of several stocks, which is difficult to accomplish. Also, purchasing the call and then immediately exercising it is not riskless since the relevant index value is also its value at the close.

Empirical tests of put-call parity can then be performed by computing the following values;

$$\varepsilon_1 = C_a - P_b + X e^{-rT} - I e^{-DT} \tag{4}$$

$$\varepsilon_2 = P_a - C_b - X e^{-rT} + I e^{-DT} \tag{5}$$

$$\varepsilon_3 = C_a - I + X \tag{6}$$

If the options are priced correctly, then ε1, ε2, and ε3 should be nonnegative. If any of the ε_i are negative, then there is a type i violation.

DATA

To eliminate problems of non-synchronous prices, intradaily data on index options is used. Employing intradaily observations on the derivative securities lends greater credibility to the empirical tests than the use of end-of-day observations.

The intradaily S&P 500 index option data used in this study are taken from the Chicago Mercantile Exchange (CME) tapes which consist of time-stamped SPX put and call trade prices and bid and ask quotes for each trading day from January 2, 1990 to June 3, 1996. Bid-ask quotes of put and call options are assumed to be valid until a trade occurs. For each SPX put and call option transaction, the bid/ask transaction price, the time at which the transaction took place, the exercise price, and the expiration date, are recorded. To construct the right portfolios that will be used to test for Type 1 and Type 2 violations, the bid (ask) call option transactions are matched with the nearest ask (bid) put option transactions that have the same maturity date and exercise price. Intraday S&P 500 cash index levels, updated every 15 seconds, are provided by the New York Stock Exchange (NYSE). The combined put-call transactions are then merged with index quotes that have the nearest time-stamp to the index call options and are within 10 seconds of the SPX call time-stamp. The requirement that transaction prices of the three instruments match up in time constrains the sample to a total of 18,864 portfolios to test for Type 1 violations, and 18,936 portfolios to test for Type 2 violations. Portfolios used to test for Type 3 violations, were constructed differently since they consisted only of index call options and their underlying security. 81, 670 portfolios were used to test for Type 3 violations. Overall, there were a total of 119,470 different portfolios used to conduct the study.

Dividend data for the S&P 500 index were collected from the Standard and Poor's 500 Information Bulletin. In dealing with index options the dividend structure of the underlying asset would seem more appropriately specified as being a continuous yield. Therefore, letting I be the current level of the index and D its dividend yield, the capital value of the index is $I\,e^{-DT}$.

Interest rate data are gathered from Bloomberg and assumed to be constant intraday. The borrowing and lending rates are also assumed to be equal. For 1- to 120-day maturities, the three-month treasury bill interest rate was used. For maturities that are greater than three months, the six-month treasury bill rate was applied.

The frequency distribution of the sample by year, contract maturity category, and out-, at, and in-the money category is provided in Table 1.

Table 1: Distribution by Year, Maturity Category, and Moneyness Category of Intraday Observations for S&P 500 Index Put and Call Option and Index Prices Matched in Time

	Distribution of Observations by Year						
	1990	1991	1992	1993	1994	1995	1996
Sample 1	4631	2521	3446	2655	2675	2138	800
Sample 2	4705	2537	3304	2635	2496	2412	848
Sample 3	15714	14332	12709	10487	11661	11068	5699

	Distribution of Observations By Maturity Category				
	Day 0	1 - 7	8 – 15	16 – 45	> 45
Sample 1	362	2590	3856	8630	3428
Sample 2	368	2804	4044	8585	3136
Sample 3	1013	8618	11950	32613	27476

	Distribution of Observations By In, Out, and At the Money Category		
	At	In	Out
Sample 1	12	7762	11092
Sample 2	4	8375	10558
Sample 3	26	21142	60502

There are two potential problems in using intraday data over an entire trading day. First, the trading mechanism at the opening of the day at the CBOE differs from the trading mechanism during the rest of the day. The opening mechanism is a clearing transaction in which all market orders and relevant limit orders are executed at a single opening price, whereas the trading mechanism over the rest of the day is a continuous trading mechanism with orders executed in the sequence of arrival. Thus, intraday PCP quotes at the CBOE opening are generated by two different trading mechanisms. Amihud and Mendelson (1987) and Stoll and Whaley (1990) document that differences in trading mechanisms affect equilibrium prices on the NYSE, as well as traders' ability to execute orders at desired prices. Also , Stoll and Whaley (1990) document that trading in some S&P stocks stops about 15 minutes before the NYSE closes.

EMPIRICAL RESULTS

A given put-call combination can be classified as a violation where ε_1 is negative, a violation where ε_2 is negative, a violation where ε_3 is negative, or a non-violation in which ε_1 , ε_2 and ε_3 are nonnegative. Of the 37,800 put and call portfolios considered, 6,135 portfolios had violations where ε_1 is negative, 14,322 portfolios had violations where ε_2 is negative. Only 131 of the 81,670 portfolios examined had violations where ε_3 is negative. Transaction costs, other than the bid-ask spread, were not included in the computations but will be discussed later.

Since the portfolios are guaranteed to produce nonnegative cash flows at expiration, the presence of a negative ε_1 or a negative ε_2 or a negative ε_3 represents a positive cash inflow today of the amount of $-\varepsilon_1$ or ε_2 or $-\varepsilon_3$. To determine whether these values are significantly different from zero, the t-statistics for the distribution of the mean values of ε_1, ε_2, and ε_3 were computed. The results are presented in Table 2.

Table 2: Put-Call Parity Violations

	Number of observations	Frequency of violation	Mean [a]	Std. Dev.	t-statistic	p-value
Type 1	18,866	6135	42.365	45.673	72.652	0.0001
Type 2	18,937	14322	102.47	96.857	126.605	0.0001
Type 3	81,670	131	56.007	138.345	4.633	0.0001

a A violation should occur when $\varepsilon_1$or $\varepsilon_2$or ε_3 are negative. The data and discussion in the text are presented with the sign reversed in order to facilitate the presentation.

Table 2 shows that Type 2 violations are more frequent and higher in magnitude than Type 1 violations. The average violation per contract for ε_1 was \$42.36 while the average violation for ε_2 was \$102.47. Both figures are significantly different from zero at the 1% level. Using almost the same number of pairs of puts and calls, it is found that Type 2 violations take place 75.63% of times and Type 1 violations occur in only 32.52% of the cases. A violation on ε_1 would be exploited by assuming short positions in the index and the put and long positions in risk free bonds and the call. A violation on ε_2 would be exploited by taking long positions in the index and a put and short positions in the call and risk free bonds. Therefore, since a Type 2 violation would be easier to exploit, it would be most likely to occur less often than a Type 1 violation. Similar to Klemkosky and Resnick (1980), the results show that Type 2 violations are more frequent than Type 1 violations.

Type 3 violations are less frequent than the other violations. Only 131 violations were detected. The average dollar size for ε_3 was \$56.00. This value is also significant at the 1% level. These violations measure the infraction of the lower boundary condition for a call option. They are much easier to exploit than Type 1 and Type 2 violations. If a Type 3 violation occur, arbitrage profits could be made by purchasing the call and selling the index. If markets were functioning properly, one would expect to find few, if any, Type 3 violations and more Type 1 and Type 2 violations.

1. The effect of Option Maturity:

In Table 3, the total number of violations by type and days to maturity are presented, along with the average dollar violation per contract.

Table 3: The Effects of Option Maturity

	Violation								
	Type 1			Type 2			Type 3		
Maturity (days)	No.	%	Avg. $ of Violation	No.	%	Avg. $ of Violation	No.	%	Avg. $ of Violation
0	84	23.20	43.464	315	85.60	143.038	37	3.65	35.973
1 – 7	644	24.86	32.308	2390	85.24	118.044	75	0.87	39.440
8 – 15	1157	30.01	37.790	3370	83.33	107.928	4	0.03	14.000
16 – 45	2851	33.04	41.974	6499	75.70	101.159	12	0.04	170.667
> 45	1399	40.81	51.392	1748	55.74	68.218	3	0.01	314.667
Total	6135			14322			131		

Maturity Category

	0		1 – 7		8 –15		16 – 45		> 45	
Dollar Amount Of Violation [A]	NO.	%	No.	%	No.	%	No.	%	No.	%
\$0 - \$30	102	23.39	899	28.59	1305	28.80	2969	31.71	1206	38.29
\$30 - \$70	92	21.10	761	24.48	1277	28.18	2847	30.41	1055	33.49
> \$70	242	55.51	1459	46.93	1949	43.02	3546	37.88	889	28.22
Total	436		3109		4531		9362		3150	
% of Violations [B]	66.48%		66.71%		66.91%		62.51%		50.94%	

A Violations are expressed in dollar units where one transaction represents 100 calls, 100 puts, and 100 "units" of the index.
B % of violations is the weighted average of the frequency of a type "i" violation per each class of maturity. The weights are calculated as the number of violations per type of violation divided by the total number of violations.

The results in the top portion of Table 3 reveal that for Type 1 violations, the relationship between the number of days to maturity and the frequency of violations is positive. In this table, the frequency of a violation (%) is calculated as the frequency of a Type "i" violation for a given option maturity category. For instance, to test for a Type 1 violation occurring on "Day 0", 362 portfolios were used. Of these 362 portfolios, 84 Type 1 violations were detected. Thus the frequency of a Type 1 violation occurring on "day 0" is 23.20% (or 84/362). It is observed that the frequency of a Type 1 violation increases monotonically with the number of days left to the option maturity. In contrast, this relationship is negative for both Type 2 and Type 3 violations. Most of these violations take place on the expiration day. For instance, 85.60% of the portfolios used to test for the occurrence of a Type 2 violation on the expiration day, compared to 55.74% of the portfolios that fall in the maturity category of 45 days or more, violated the second Put-Call Parity condition that was developed in this study. Similar results are observed for Type 3 violations where the frequency of a violation decreases with the number of days left to maturity with most of the violations occurring during the last week of the option's life.

As for the relationship between the number of days left to maturity and the average dollar size of a violation, it is observed that this relation is negative for Type 2 violations and positive for Type 3 violations for all maturity categories. Most arbitrage profits from a Type 2 violation are made on expiration day whereas the highest arbitrage profits from a Type 3 violation are realised when the option is more than 45 days to maturity. For Type 1 violations and for option maturities that are one day or more, the average dollar size of the violation increases with the number of days left to maturity with arbitrage profits being highest in the last maturity category. However, and similar to Type 2 violations, arbitrage profits are also high on the expiration day.

In the bottom portion of Table 3, the relation between option maturity and dollar size of violation is investigated. For the first two classes of Dollar Amount of Violation, it is seen that as the maturity of the option increases, the frequency of the violations also increases. If we look at the (0 - $30) class, we can see that for the 0-days to maturity, the frequency of a less than $30 violation is 23%, whereas for options with maturities greater than 45 days, the frequency of a less than $30 violation is 38%. The opposite relation is observed when the dollar amount of violation exceeds $70; the frequency of the dollar size of violation decreases as the option maturity increases. Almost 56% of the violations that occur on the expiration day compared to 28% of the violations with more than 45 days to maturity, exceed $70 in magnitude. It is also observed that for option maturities that are less than 45 days, most violations have a dollar amount that is greater than $70 per contract. This implies that as the life of the option gets shorter, the average size of a violation is higher in magnitude.

Overall, the frequency of a violation is almost the same for the first three maturity categories (66.48% for "day 0", 66.71% for "1 to 7" days-, and 66.91% for "8 to 15" days-to maturity). However, the frequency of observing a violation decreases to 62.51% for options that have 16 to 45 days to maturity and goes down to 50.94% for options that have 45 days or more to maturity. Thus, the frequency of violations decreases with option maturity with the majority of the violations occurring when the option's life is two weeks or less.

2. In-, At-, and Out-of-the-Money Options:

The propensity for violations to occur when the option is in-, at- or out-of-the money was examined. Out of the total sample of option transactions, there are 30 at-the-money options, 29,512 in-the-money options, and 71,054 out-of-the-money options. Table 4 divides the sample by type of violation and out-, at-, and in-the-money category.

Table 4: The Effect Of The Option's Category

	Violation								
	Out-of-the Money			At-the Money			In-the Money		
Type of Violation	No.	%	Avg. $ of Violation	No.	%	Avg. $ of Violation	No.	%	Avg. $ of Violation
1	3463	31.22	44.64	4	33.33	74.46	2668	34.37	39.36
2	8211	77.77	114.68	3	75.00	30.39	6108	72.93	86.09
3	0	0.00	0	0	0.00	0	131	0.22	56.01
Total	11674			7			8907		
% [b]		63.40 %			62.11 %			60.98 %	

b % of violations is a weighted average of the number of violations per category. The weights are calculated as the number of violations per type of violation divided by the total number of violations.

In Table 4, the frequency of a violation is calculated as the frequency of a type "i" violation per a given "moneyness" category. For instance, 11092 portfolios that fall in the "out-of-the money" category were used to test for a Type 1 violation. Of these portfolios, a Type 1 violation was observed 31.22% of the time. The results in Table 4 reveal that Type 1 violations are more frequent for in-the money options. In contrast, most of Type 2 violations are observed for out-of-the money options. Similar to Puttenon (1993), all Type 3 violations occurred for in-the-money options. However, the frequency of these violations is very small. For all types of violations, the average dollar size is higher for out-of-the money options than for in-the money options. Also, the highest magnitude or possible arbitrage profit is detected for out-of-the money options and Type 2 violations.

Overall, it is observed that the frequency of violation per "moneyness" category is almost the same with out-of-the money options having the highest frequency of violation (63.40%) and in-the money options having the lowest frequency of violation (60.98%).

Table 5 divides the sample by type of violation, number of days to maturity, and out- and in-the money options. Given the low frequency of at-the-money options, they are not reported as a separate group[36].

The top portion of Table 5 show that the frequency of Type 1 violations increases with the number of days to maturity. Only 24.31% of portfolios with zero days to maturity violate the first Put-Call Parity condition, whereas 40.81% of portfolios with maturity of 45 days or more, have Type 1 violations. This frequency is higher for in-the money options than for out-of-the money options for all maturity categories. For instance, on the expiration day, 36.17% of in-the money options versus 16.82% of out-of-the money options violate the first parity condition. As for the average dollar size of a Type 1 violation, it is observed that most of these violations are $30 or less. It is also observed that the higher the average dollar size, the lower the frequency of a Type 1 violation.

Again the relationship between the number of days to maturity and the frequency of Type 2 violations is negative. In other words, as the life of the option increases the frequency of detecting a Type 2 violation goes down. However, this time, the frequency of observing a Type 2 violation per a given maturity category is higher for out-of the money options than in-the money options for all maturity categories except for options

[36] At-the-money options are included with in-the-money options.

that have 45 days or more to maturity. It is also observed that most of Type 2 violations have an average dollar size of $70 or more.

As noted before, all Type 3 violations are observed for in-the money options. Most of these violations occur when the life of the option is less than one week. However, out of the 131 detected Type 3 violations, 63.36% are less than $30 in dollar size and only 15.27% are more than $70 on average.

Table 5: Number of Violations By type of Violation, Dollar Amount of Violation, Number of Days to Maturity, and The Out, At, and In-the-Money Category

Dollar Amount Of Violation			0		1 – 7		8 – 15		16 - 45		> 45	
			In	Out	In	Out	In	Out	In	Out	In	Out
	No.	%	Violation Category: Type 1									
0 – 30	3021	49.24	27	14	227	169	294	318	640	764	205	363
30 – 70	2098	34.20	18	13	86	95	180	215	422	568	187	314
> 70	1016	16.56	6	10	30	37	60	90	186	267	101	229
% [A]	32.52%		36.17	16.82	29.42	21.14	31.69	28.71	35.23	31.47	40.15	41.24
Grand % [B]			24.31%		24.86%		30.01%		32.99%		40.81%	
	No.	%	Violation Category: Type 2									
0 – 30	3367	23.51	25	18	260	179	362	326	725	833	303	334
30 – 70	3906	27.28	19	30	270	297	452	430	824	1029	246	308
> 70	7049	49.21	45	178	526	857	713	1086	1096	1991	242	315
%	75.63%		68.46	94.96	80.43	89.46	81.53	84.88	71.88	78.58	57.36	54.47
Grand %			85.60%		85.20%		83.31%		75.69%		55.74%	
	No.	%	Violation Category: Type 3									
0 – 30	83	63.36	19	0	53	0	4	0	6	0	1	0
30 – 70	28	21.37	14	0	13	0	0	0	1	0	0	0
> 70	20	15.27	4	0	9	0	0	0	5	0	2	0
%	0.16%		7.77	0.00	1.95	0.00	0.10	0.00	0.15	0.00	0.07	0.00
Grand %			3.65%		0.87%		0.03%		0.04%		0.01%	

A the percentage of violations is calculated as the number of violations per maturity category per moneyness category divided by the number of violations per maturity category.
B the percentage of violations is calculated as the number of violations per maturity category divided by the number of total observations per maturity category

3. The effects of The Introduction of SPDRs:

Table 6 divides the sample into two sub-samples: the first (Panel A) investigates the violations by type, dollar amount, number of days to maturity, and out- and in-the-money categories before the introduction of SPDRs. Panel B looks at the relationship between the frequency and magnitude of violations and these option characteristics.
To assure that the two panels are comparable, we looked at the different relationships that were discussed in the previous sections and we found that the same relations exist for before and after the introduction of SPDRs for all types of violations.

After the introduction of SPDRs, the frequency of Type 1 violations is lower for options' maturities that are less than one week and higher for those that are more than one week. Overall, it seems that the frequency of a Type 1 violation has increased from 31.90% in the first period to 33.40% in the second period. Again, the frequency of Type 1 violations is higher for in-the money options. When looking at the dollar amount of the violations, it is observed that most violations are less than $30 in dollar size for before and after the introduction of SPDRs (52.99% and 44.39% respectively). The frequency of violations that are less than $70 in magnitude is reduced (from 86.82% to 79.06%), but violations more than $70 in value have increased from 13.18% to 20.94%.

Table 6: Violations Before and After the Introduction of SPDRs

Before The Introduction of SPDRs:

Panel A: Number of Violations By type of Violation, Dollar Amount of Violation, Number of Days to Maturity, and The Out, At, and In-the-Money Category

Dollar Amount Of Violation			0		1 – 7		8 – 15		16 – 45		> 45	
			In	Out	In	Out	In	Out	In	Out	In	Out
	No	%	Violation Category: Type 1									
0 – 30	1834	52.99	13	8	127	111	183	166	356	446	158	266
30 – 70	1171	33.83	9	9	44	46	91	112	225	291	130	214
> 70	456	13.18	4	9	15	18	17	32	60	106	59	136
%	31.90%		34.21	20.00	29.90	21.50	31.49	25.85	34.35	29.79	40.63	40.18
Grand %			25.24%		25.14%		28.31%		31.60%		40.34%	
	No	%	Violation Category: Type 2									
0 – 30	2048	24.85	12	11	143	89	211	170	449	493	219	251
30 – 70	2262	27.44	9	10	139	139	239	245	486	605	168	222
> 70	3932	47.71	26	86	318	468	391	616	597	1097	144	189
%	76.34%		61.04	90.68	82.19	89.23	84.02	85.63	74.37	79.99	60.00	55.26
Grand %			78.97%		85.83%		84.90%		77.58%		57.27%	
	No.	%	Violation Category: Type 3									
0 – 30	43	65.15	9	0	28	0	2	0	3	0	1	0
30 – 70	13	19.70	6	0	6	0	0	0	1	0	0	0
> 70	10	15.15	3	0	2	0	0	0	4	0	1	0
%	0.15%		7.50	0.00	1.67	0.00	0.09	0.00	0.18	0.00	0.07	0.00
Grand %			3.28%		0.75%		0.03%		0.05%		0.01%	

After The Introduction of SPDRs:

Panel B: Number of Violations By type of Violation, Dollar Amount of Violation, Number of Days to Maturity, and The Out, At, and In-the-Money Category

Dollar Amount Of Violation			0		1 – 7		8 – 15		16 – 45		> 45	
			In	Out	In	Out	In	Out	In	Out	In	Out
	No.	%	Violation Category: Type 1									
0 – 30	1187	44.39	13	7	100	58	111	152	284	318	47	97
30 – 70	927	34.67	9	4	42	49	89	103	197	277	57	100
> 70	560	20.94	2	1	15	19	43	58	126	161	42	93
%	33.40%		36.92	13.33	28.86	20.66	31.93	32.23	36.22	33.59	39.04	43.67
Grand %			23.23%		24.52%		32.10%		34.71%		42.00%	
	No.	%	Violation Category: Type 2									
0 – 30	1319	21.69	13	8	118	90	151	156	276	340	84	83
30 – 70	1644	27.04	10	20	131	159	213	185	338	424	78	86
> 70	3117	51.27	19	92	208	389	322	470	499	894	98	126
%	74.73%		79.25	100	78.39	89.86	78.67	83.95	68.70	76.79	52.63	52.77
Grand %			93.64%		84.69%		81.45%		73.33%		52.71%	
	No.	%	Violation Category: Type 3									
0 – 30	40	61.15	10	0	25	0	2	0	3	0	0	0
30 – 70	15	23.07	8	0	7	0	0	0	0	0	0	0
> 70	10	15.38	1	0	7	0	0	0	1	0	1	0
%	0.17%		8.05	0.00	2.29	0.00	0.11	0.00	0.11	0.00	0.06	0.00
Grand %			4.09%		1.02%		0.04%		0.03%		0.01%	

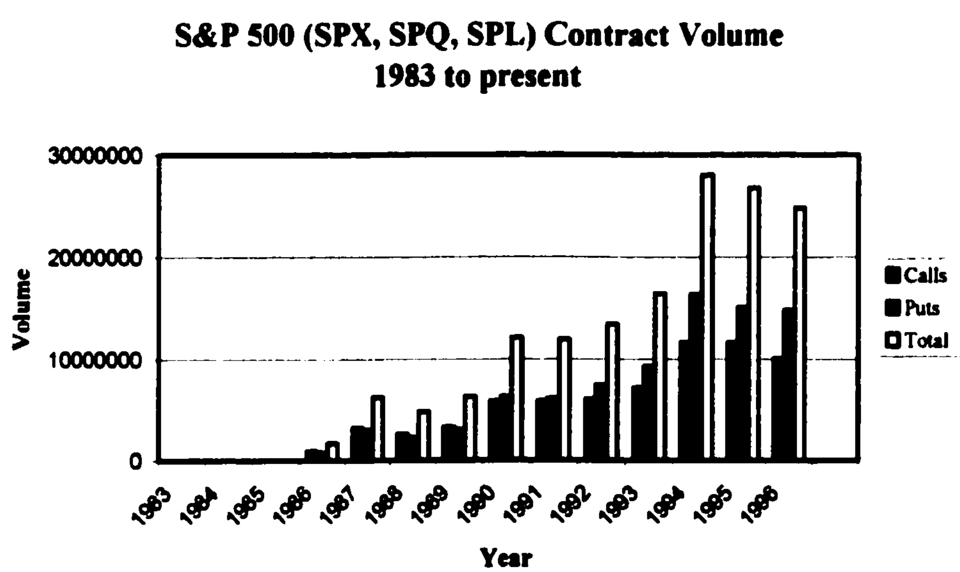
After the introduction of SPDRs, the overall frequency of Type 2 violations slightly went down from 76.34% to 74.73%. The frequency is also lower for all maturity categories. Again, the frequency of violations decreases with the number of days to maturity. Also, the frequency of violations is higher for out-of-the money options than for in-the money options for all maturity categories. Violations that are more than $70 in value are more frequent after the introduction of SPDRs. In Panel A, most violations have dollar amount that is more than $70 (47.71%), whereas in Panel B, 51.27% of the violations have a dollar value that is more than 70 dollars. This suggests that after the introduction of SPDRs, the magnitude of the violations has increased.

The frequency of Type 3 violations is almost the same in Panel A and Panel B. Violations were detected only for in-the-money options and most of these violations are less than 30 in dollar size. Even though the change in frequency is not significant, one can notice that, after the introduction of SPDRs, the frequency of Type 3 violations increased for less than two weeks option maturities and increased for more than two weeks option maturities.

To summarize, the results in Panel A and Panel B show that before and after the introduction of SPDRs, the relationships between the frequency of a Type "i" violation and its average dollar size and the different examined option's characteristics, are the same. However, the magnitude of all types of violations has increased in the second period. The frequencies of both Type 1 and Type 3 violations have increased and the frequency of Type 2 violations has decreased. The effect of the introduction of SPDRs will be further discussed in the following section.

THE NATURE OF THE MARKET OVER TIME:

Figure 1 shows the annual trading volumes of SPX options. As one can see, the observed trading volumes exhibit an increasing pattern. In 1983, the volume of trading in S&P 500 index options totalled over 14,093 contracts. Volume grew to over 12 million, 16 million, and 24 million in 1990, 1993, and 1996 respectively.



Given the rapid growth in volume of S&P 500 index options trading over the sample period, it might be expected that the nature of the market has changed as investors and traders became more familiar with the pricing of options and the market gained more liquidity. In addition to that, with the existence of the S&P Depository Receipts, index arbitrage is easier to accomplish than before. Instead of trying to replicate the index by simultaneously purchasing or selling the component stocks with the proper weights through numerous transactions, investors and arbitrageurs can "trade" the index by conducting only one transaction through SPDRs. As a result, one might expect to detect a decline in the frequency and magnitude of the violations.

Table 7: Frequency of Violations

Year	Violation Type 1	Violation Type 2	Violation Type 3	No. Of Transactions
	44.948	126.035	125.083	20419
1990	(53.965)	(105.267)	(343.989)	
	(1223)	(3672)	(12)	
Frequency	4631	4705	15714	
	42.394	99.298	70.733	16869
1991	(57.005)	(74.527)	(74.618)	
	(514)	(2178)	(15)	
Frequency	2521	2537	14332	
	35.247	50.030	23.421	16013
1992	(38.658)	(43.764)	(25.903)	
	(1623)	(2198)	(38)	
Frequency	3446	3304	12709	
	33.731	53.352	36.250	13122
1993	(34.690)	(43.251)	(49.287)	
	(806)	(2094)	(20)	
Frequency	2655	2635	10487	
	53.664	71.022	36.892	14157
1994	(45.755)	(60.486)	(37.850)	
	(1324)	(1472)	(37)	
Frequency	2675	2496	11661	
	37.355	165.317	337.400	13480
1995	(34.915)	(123.486)	(340.705)	
	(454)	(2020)	(5)	
Frequency	2138	2412	11068	
	56.242	186.527	27.000	6547
1996*	(50.664)	(119.622)	(8.524)	
	(191)	(688)	(4)	
Frequency	800	848	5699	

Note: The numbers in parentheses are the estimated standard deviation and the number of Type i violations per year, respectively.

* The sub-sample for 1996 is from Jan. 2 to Jun. 3, 1996

However, looking at the evolution of the market during the period covered in this study (Table 7), it is observed that the number of matched index option transactions has decreased over time. This suggests that trading in the index option market is more frequent in the earlier years.

The first hypothesis to be tested examines whether the probability of observing a violation changed over time. If investors have become more knowledgeable about the pricing of index options, then, ceteris paribus, it might be expected that the probability of a violation occurring would have decreased over time. However, other things did not remain constant since there was a rapid growth not only in index option trading but also in a variety of optionable securities. Thus both liquidity and the ability to analyse and price index options may actually have decreased with the growth in options markets. The null hypothesis is that there is no change, and the alternative hypothesis is that the probability of observing a violation has changed.

The sample was split into two three-year intervals for before and after the introduction of SPDRs. The probability of a violation occurring is estimated by the frequency of a given type of violation to the total number of transactions used to calculate that violation during the interval. Assuming that violations of a given type are independent events, a Z-statistic for testing the equality of the probabilities for two Bernoulli random variables is constructed; the statistic is asymptotically normally distributed. The results are shown in Table 8 where it is seen that the null hypothesis, that the probability of a violation has not changed over the six-year period, can be rejected. The results indicate that while the probability of a Type 1 violation has significantly increased over time, the probability of a Type 2 violation has decreased. However, Type 2 violations are still more frequent than Type 1 violations. The frequency of occurrence of a Type 3 violation has also increased but not significantly.

Table 8: Frequency of Violations Test

Year	Type 1	Violation Type 2	Type 3
Before Jan 90 – Jan 93	3461 31.89% (10856)	8242 76.31% (10800)	66 0.15% (43641)
After Feb 93- Jun 96	2674 33.38% (8010)	6080 74.72% (8137)	65 0.17% (38029)
Z statistic	-2.177*	2.529*	-0.701

The numbers in parentheses are the total number of transactions used to calculate Type i violation.
* Statistically significant at the 5% level.

Those results should be interpreted with caution. One cannot conclude that the introduction of SPDRs had no effect on the options market. In fact, the increase in the frequency of violations might be due to other market factors. In order to lessen the effect of other factors that might spur violations of arbitrage boundary or Put-Call Parity conditions, we focused on just one year before and one year after the introduction of SPDRs. The sample was divided into two one-year periods and the probability of a Type "i" violation happening was recalculated again using the same procedure as before. Table 9 summarises the findings of the frequency of violations test. It can be observed from this table that, opposite to the above results, the probability of a Type 1 and the probability of a Type 3 violation have decreased whereas the probability of a Type 2 violation had increased.

Table 9: Frequency of Violations Test			
		Violation	
Year	Type 1	Type 2	Type 3
Before Jan 92 - Dec 92	1621 47.09% (3442)	2197 66.55% (3301)	38 0.30% (12679)
After Feb 93 – May 94	1143 35.15% (3252)	2333 73.53% (3173)	28 0.21% (13342)
Z statistic	9.922*	-6.117*	1.440

The numbers in parentheses are the total number of transactions used to calculate Type i violation.
* Statistically significant at the 5% level.

The second hypothesis concerns the magnitude of the violations. Irrespective of whether the probability of a violation occurring has changed or not, the mean magnitude of the violations of a given type might have changed over the six-year period. The null hypothesis is that the mean value has not changed, and this is tested against the alternative hypothesis that the mean has changed. The test statistic is described by a t-distribution which, given the large number of observations, is asymptotically normally distributed. The results are shown in Table 10.

Table 10: Mean Magnitude of Violations Test				
		Violation		No. of
Year	Type 1	Type 2	Type 3	Transactions
Before Jan 90 - Jan 93	39.426 (47.419) (3461)	96.681 (89.293) (8242)	52.500 (152.229) (66)	65282
After Feb 93 - Jun 96	46.168 (43.021) (2674)	110.319 (105.749) (6080)	59.569 (123.756) (65)	54167
t statistic	-5.820** (0.0001)	-8.141** (0.0001)	-0.292* (0.771)	

The numbers in parentheses are the standard deviation and the total number of Type i violations per interval of time.
* The variances are found to be equal at the 1% significance level
** The variances are found to be unequal at the 1% significance level.

The null hypothesis can be rejected for Type 1 and Type 2 violations. The difference in mean magnitude of violations between the two time intervals is different from zero at the 1 percent level of significance. The violations occurring in the second interval, that is after the introduction of SPDRs, have a higher dollar size, and also a higher variability. This implies that both the magnitude and the variability of the violations have increased over time. The null hypothesis is accepted for Type 3 violations implying that the difference in mean magnitude between the two time intervals is not significantly different from zero.

The same tests were performed on a two one-year sample. The results are shown in Table 11.

Table 11: Mean Magnitude of Violations Test

Year	Violation Type 1	Type 2	Type 3	No. Of Transactions
Before	35.202	50.048	23.421	20337
Jan 92 - Dec 92	(38.661)[a]	(43.765)	(25.902)	
	(1621)[b]	(2197)	(38)	
After	40.569	53.426	34.321	20119
Feb 93 - May 94	(38.111)	(42.821)	(42.594)	
	(1143)	(2333)	(28)	
t statistic	-3.615*	-2.625*	-1.200**	
	(0.0003)[c]	(0.0087)	(0.2368)	

The numbers in parentheses are (a) the standard deviation, (b) the total number of Type i violations per interval of time, and (c) the p-value.
* The variances are found to be equal at the 1% significance level
** The variances are found to be unequal at the 1% significance level.

Again, the null hypothesis that the mean value of violations has not changed over time, is rejected. The difference in mean magnitude of violations between the first and second period is statistically different from zero for Type 1 and Type 2 violations at the 1 percent level of significance. This implies that the average value has changed over time. More precisely, since the difference is positive, one can conclude that the magnitude of a Type 1 or a Type 2 violation has increased. The null hypothesis could not be rejected for Type 3 violations. This implies that there was no significant difference between the two periods.

The results suggest that over the six-year period, the frequencies of Type 1 and Type 3 violations, have increased. Moreover, the magnitude of all types of violations has increased implying that those detected arbitrage opportunities are more profitable in the second period. The volume of index option trading underwent rapid growth during the six -year-period. In 1990, SPX volume was around 12 million contracts. In 1996, trading volume grew to almost 25 million contracts. The results might be due to the inability of the market to adjust to such changes. When focusing on one year before and one year after the introduction of SPDRs, evidence suggests that the frequencies of Type 1 and Type 3 violations have decreased over time. However, the dollar size of all violations is still higher in the second time interval.

The above results suggest that put-call parity violations are frequent and a potential source of abnormal returns for index options traders. Again, these results must be interpreted with caution. A number of points should be noted:

First, the dollar size of the violations discussed so far represents ex post figures. In fact, the profitability of those arbitrage opportunities identified upon the presence of a violation is somewhat questionable. Since there is no guarantee that the prices used in the arbitrage strategy are equal to the prices at the time of the violations, there is no guarantee that the arbitrage opportunities will still be profitable. Hence, the occurrence of a violation should rather be considered as a signal. As a consequence, one should look at the profitability of the trading strategy implemented upon the observation of the signal.

Second, although the transactions required to build the portfolio should be made simultaneously, the way the data file was set in this study, forces a sequential strategy. The call option trade was matched with the closest put option trade that occurred at or after the call option trade. Then, the combined call-put trade was matched with the closest cash index trade. Due to this sequential order and the resulting time delays in achieving the required portfolio, the risk of the strategy is increased. This problem of non-simultaneity of the data biases the results against finding that the market is inefficient.

Third, in addition to time delays that might be caused by the way the portfolios are constructed in this study, Stephan and Whaley (1990) and Chan, Chung, and Johnson (1993) find that stocks lead options by fifteen to twenty minutes[37]. Chan, Chung, and Johnson (1993) propose an explanation for the lead of stocks over options. Since option prices do not move as much in absolute terms as the underlying stock, a stock price will not cause any move in the option unless the stock price change is big enough to cause the market price of the option to move a tick (the minimum price change)[38]. Thus, the option will trade after the stock has made more than one move in the same direction. In other

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[37] Manaster and Rendleman (1982), Bhattacharya (1987), Anthony (1988), and Finucane (1991) find evidence that options lead stocks.

[38] The minimum move or tick for a stock is typically one-eight. The tick for options with prices greater than three dollars is also an eight, but entails a much larger percentage move in the option price. Thus, small moves in the stock will usually not be immediately reflected in the option because the change in theoretical value of the option is less than the tick and so the option does not trade. For options with prices below dollars, the tick is one-sixteenth, but the same effect should still occur.

words, the tick size prevents options from trading immediately in response to small price changes. This infrequent trading of options might cause put-call parity violations to arise.

Finally, to determine the actual extent of the financing required to build the appropriate arbitrage portfolios, transactions costs should be included in the analysis. Even though, bid and ask spreads for the index options were used, additional costs would also be incurred, for instance, on replicating the index or on borrowing or simply on commissions. It is not clear whether the estimated arbitrage profits can absorb those overlooked costs. The following section discusses the profitability of the detected arbitrage opportunities after accounting for transaction costs.

TRANSACTION COSTS:

For index options, transaction costs are not fixed but vary with the price of the option. Also, in the index option market, investors pay commissions twice; at the time of initial trade and then to close out the position (unless the position is allowed to expire unexercised). In general, one-way commission and bid/ask spreads are all combined and are charged to institutional investors. In this section, the same transactions costs employed by Lee and Nayar (1993) are used. In the empirical tests, it is assumed that double the one-way transaction costs (one-way commissions plus the bid/ask spread) are incurred even if the option is allowed to expire unexercised. Thus, an overestimate of transaction costs is used. Violations that arise despite this indicate strong evidence of existence of arbitrage opportunities. To be conservative, Lee and Nayar (1993) used the costs charged by a typical leading full service (not discount) commission brokerage firm. Their estimates of transactions costs that are employed are consistent with those charged by Merrill Lynch and are the following:

> Base commission = (\$14 + 0.016 * option price * \$100) per contract
> Subject to a maximum of 17% of principal value.
> Less: 0.03 * base commission
> With the following exceptions:
> If the commission calculated is less than \$30, then there is a minimum charge of: \$30 on orders of principal value of \$187.50 and greater or 16% of principal value on orders less than \$187.50. The maximum charge per contract can never exceed \$92.00

In Kamara and Miller (1995), commissions and bid-ask spreads of the S&P 500 component stocks are estimated to be 0.38%, on average, of S&P 500 cash index value. Also, Kawaller (1991) estimates the transaction costs of replicating the S&P 500 index to be 0.36% of the S&P portfolio value.

In this study, tests are conducted using Lee and Nayar (1993) transaction cost structure for index options. Kamara and Miller (1995) estimates for commissions and bid/ask spread of replicating the S&P 500 are applied. Rearranging condition (4), (5), and (6) to account for transactions costs lead to the following no-arbitrage relationships:

$$\varepsilon_1 = C_a - P_b + X\,e^{-rT} - I\,e^{-DT} + (T_c + T_p + T_I) \tag{4 a}$$

$$\varepsilon_2 = P_a - C_b - X\,e^{-rT} + I\,e^{-DT} + (T_c + T_p + T_I) \tag{5 a}$$

$$\varepsilon_3 = C_a - I + X + (T_c + T_I) \tag{6 a}$$

Where T_c, T_p, and T_I are the transaction costs of buying or selling call options, put options and the S&P 500 index respectively. Again all the ε_I are supposed to be positive otherwise arbitrage opportunities exist.

As one can see from Table (12), when the assumed actual transaction costs are used, the majority of the sample appears to comply with the no-arbitrage bounds developed earlier. There are only 27 (0.14% of Sample 1) Type 1 violations and 846 (4.48% of Sample 2) Type 2 violations compared to 6135 and 14322 respectively. Only 5 violations of the lower boundary condition (Type 3) were detected. The average arbitrage profits from these opportunities amount to \$88.56, \$56.03, and \$391.23 per contract, respectively.

The hypothesis that the mean value of the arbitrage profit is different from zero, is tested. The results indicate that the mean magnitude of Type 1 and Type 2 violations is statistically different from zero at the 1% level of significance. These profits are defined as ex post profits because it is assumed that trades can be consummated at those very prices that are identified as profitable opportunities by the arbitrage model. In practice, transactions can rarely be conducted at the prices that violate the no-arbitrage bounds but instead at the next occurring trades. On an ex ante basis, where the ex post violations are used as a signal to form arbitrage positions, most of the Finance literature in this area[39], show that the profits disappear, and the transactions produce increasing losses as time elapses after the initial violation. Thus, the only way one can make profit out of these arbitrage opportunities is to act at the same time of the ex post signal. Unfortunately, this might be possible only in theory.

[39] Galai (1978), Klemkosky and Resnick (1980), Halpern and Turnbull (1985), Chance (1987), Puttonen (1993)

Table 12: Put-Call Parity Violations (per contract) Using Transaction Costs

	Number of observations	Frequency of violation	Mean [a]	Std. Dev.	t-statistic	p-value
			Type 1 Violation			
	18,864	6135	42.365	45.673	72.652	0.0001
Assuming No Transaction Costs			Type 2 Violation			
	18,936	14322	102.47	96.857	126.605	0.0001
			Type 3 Violation			
	81,670	131	56.007	138.345	4.633	0.001
			Type 1 Violation			
	18,864	27	88.668	130.262	3.573	0.0015
Assumed Transaction Costs			Type 2 Violation			
	18,936	846	56.036	49.566	32.883	0.0001
			Type 3 Violation			
	81,670	5	373.945	391.230	2.137	0.0994

a A violation should occur when $\varepsilon_1$or $\varepsilon_2$or ε_3 are negative. The data and discussion in the text are presented with the sign reversed in order to facilitate the presentation.

After accounting for transaction costs, whether SPX options have better conformed to their theoretical value after the introduction of SPDRs is assessed once more by comparing the frequency and magnitude of the occurring violations in the first and second half of the testing period. In Table 13, the decrease in the frequency and magnitude of Type 1 and Type 2 violations is evident. In the second period, only 0.04% of Type 1 violations and 3.06% of Type 2 violations are detected compared to 0.22% and 5.53% in the first period. The decrease in the frequency of Type 1 and Type 2 violations is statistically significant at the 1% level. This indicates that violations of the no-arbitrage conditions are less frequent after the introduction of the Standard and Poor's Depository Receipts.

Table 13: Frequency and Magnitude of Violations: Before and After the Introduction of SPDRs

Year	Violation Type 1	Type 2	Type 3
Before	24	597	2
Jan 90 – Jan 93	95.381	60.691	520.389
	(10856)	(10800)	(43641)
After	3	249	3
Feb 93- Jun 96	34.968	44.877	276.314
	(8010)	(8137)	(38029)
Z statistic	3.297*	8.137*	-0.602
t-statistic	1.825**	3.821*	0.629

The number in parentheses is the total number of transactions used to calculate Type i violations.
The Z-statistic tests the hypothesis that the frequency of a Type i violation did not change over the two time periods.
The t-statistic tests the hypothesis that the true means of the two periods are the same. The underlying assumption is that the variables are normally and independently distributed within each group.
* Statistically significant at the 1% level.
** Statistically significant at the 10% level.

The null hypothesis that the mean value of a violation has not changed after the introduction of SPDRs is tested. The mean differences in the dollar size of all types of violations are negative suggesting that there is a decrease in the magnitude of the violations in the second half. The difference is statistically significant at the 1% level for Type 2 violations. For Type 1 and Type 3 violations, even though the decrease in the dollar size of the violations is apparent, it may be questionable whether the t-test remains appropriate when the number of observations is very small[40].

Thus after accounting for transactions costs, both the frequency and magnitude of violations have decreased substantially after the introduction of SPDRs. The dollar size of the violations is still positive, and as mentioned before, there is no guarantee that those profitable opportunities will persist over time. In addition to that, dividends paid on a long (short) portfolio must be reinvested (financed) by buying (selling short) additional shares of the index. The transaction cost of managing such a portfolio would surely exceed these potential returns. For example, the maximum Type 1 violation was $587.45 based on 100 units of the index valued at $39035. Thus, the abnormal return without those transaction costs is about 1.5% of the index. The maximum Type 2 violation was $645.54 based on an index portfolio worth about $46122 or a profit of about 1.4% of the index. Thus, unless the index could be replicated at a transaction cost of less than 1.4 – 1.5%, these profits could not have been obtained. The management fee of SPDRs amounts to 20 basis points which are above the estimated transaction cost. Another source of transaction costs that was not accounted for is the Treasury bill commission. Apparently, the market recognizes this fact and allows frequent violations of the put-call parity rule since transaction costs will wipe out any possible arbitrage profits. Any attempt to exploit those violations of no-arbitrage conditions will rarely succeed.

[40] Given the small number of observations (27 Type 1 violations and 5 Type 3 violations), the normality assumption is not valid anymore. The results are not statistically reliable.

SUMMARY AND CONCLUSION

The violation definitions developed earlier assume all relevant data are recorded at the same point in time. Given the absence of continuous trading in stock and option markets, any empirical test is faced with the problem of non-synchronous trading. Even though this study uses intradaily data, the problem of non-synchronous trading still persists. The reported spot index is based on the last trade price of each of the 500 stocks in the index. It does not represent the prices at which an arbitrageur could actually trade the stocks. This may lead to the illusion of arbitrage opportunities. Therefore, the results of this study, and any other studies in this area, must be carefully translated.

If an investor could enter the market and transact at the option and stock prices that generated an observed violation, then, ignoring transactions costs, it would be possible to construct a portfolio that generates positive cash flows at its creation with zero cash flows at expiration. This implies that the options market is inefficient since an investor is able to consistently earn an above normal rate of return for the level of risk taken. The ex post results of this study show that there are significant violations of the arbitrage condition and put/call parity. Even after acknowledging the difficulty of earning risk free profits due to the difficulty of replicating the index or the fact that an arbitrageur has to wait till the end of the day to know the exact payoffs of his/her arbitrage strategy, the violations that were observed were substantial.

Considering all three types of violations and assuming no transaction costs, there are four general observations that can be made. First, for Type 1 violations, there is a positive relationship between the frequency of violations and the number of days to maturity of the option. For Type 2 and Type 3 violations and similar to Galai (1978) and Halpern and Turnbull (1985), this relationship is negative. The average dollar size of the violations seems to increase with the option's maturity for Type 1 and Type 3 violations. For Type 2 violations, the average magnitude seems to decrease with the number of days to maturity. Second, violations of the Put-Call Parity are more frequent when the call options are out-of-the money. Also, the size of the violation tends to be greater for out-of-the money call options than for in-the money call options. This can be explained by the fact that out-of-the money call options are less liquid than in-the-money call options. Third, Type 3 violations are not very frequent and are observed only for in-the-money options. Fourth, when looking at the frequency and magnitude of violations before and after the introduction of SPDRs, the same relationships are detected implying that the two sample periods are comparable.

The effect of the introduction of SPDRs was first investigated in the absence of transaction costs. No solid conclusion concerning the frequency of violations could be reached at that point. However, it was obvious that the magnitude of the violations were much higher in the second period. When taking transaction costs into account, only few violations of the no-arbitrage conditions were detected. Both the frequency and the magnitude of the violations are considerably reduced after the introduction of SPDRs. However, the dollar size of these violations was still substantial.

CONCLUSION

After the introduction of SPDRs, market participants began to wonder how index participation units were going to fare in the presence of index futures, options, and mutual funds. The easy availability of a security, such as SPDRs, that tracks the movement of a stock index, such as the S&P 500, can contribute to increased activity in and market efficiency of other index related products. At the same time, if such a security provides a better substitute for other index products in tracking general market co-movement, these other index products will show reduced activity and market efficiency. This paper examines the effects of SPDRs' trading on the pricing efficiency of the S&P 500 index futures contracts and the S&P 500 index options contracts. For index futures, pricing efficiency is tested by looking at the difference between actual prices and theoretical prices as per the Cost of Carry model. As for index options, one attribute of efficiency is the frequency and magnitude of Put-Call Parity violations. These two measures are tested to observe any change or trend after the introduction of SPDRs.

Similar to MacKinlay and Ramaswamy (1988) and Bhatt Cakici (1990), we find the average daily mispricing of S&P 500 Index futures is positive but very small in magnitude. The average daily mispricing and its variability as measured by the standard deviation both significantly dropped after the introduction of SPDRs. Based on those results, we concluded that index futures mispricing has decreased and became less frequent. When looking at the average absolute value of mispricing, we observed that mispricing has indeed decreased the results were not significant. The same analysis was conducted using intradaily prices. This time we found that the average mispricing, the absolute value of the average mispricing, and their respective variances, have considerably decreased in the second half of the tested period. The mispricing series were characterized by high levels of autocorrelation and heteroskedasticity. In order to provide more rigorous tests, we modeled the mispricing series by fitting ARIMA and GARCH models. Results have shown that the ARIMA(4,0,4)-TGARCH model fits both the daily and intradaily series quite well. Based on the results of this model, we find that after the introduction of SPDRs, the S&P 500 index futures prices have much better conformed to their theoretical values.

Tests on the S&P 500 Index options show that overall, there are significant violations of the arbitrage conditions as per the Put-Call Parity. Similar to Galai (1978) and Turnbull (1985), we found a negative relationship between the options' maturity and the frequency of violations for Type 2 and Type 3 violations but not for Type 1 violations. A positive relationship between the option's maturity and the magnitude of the violation is detected for both Type 1 and Type 3 violations. Also, the dollar size of the violations tends to be greater for out-of-the money options than for in-the-money options that may be due to the fact that out-of-the money options are less liquid than in-the-money options. Similar to Puttenon (1993), all Type 3 violations occurred for in-the money options. The same relations were observed when dividing the sample into before and after the introduction of SPDRs.

The effect of SPDRs was investigated by testing two hypotheses. The first one concerns whether there was any change in the frequency of a type "i" violation after the introduction of SPDRs. The second hypothesis deals with the magnitude of a type "i" violation and tests whether there was a change in the dollar size of the violations in the second half of the testing period. Assuming no transaction costs and focusing on one year before and one year after the introduction of SPDRs, we found that, unlike the probability of a type 2 violation, the probability of a type 1 violation and the probability of a type 3 violation were reduced. As for the magnitude of these violations, it was shown that the average value of a type 1 violation and a type 2 violation had increased. Unfortunately, in this case, no clear-cut conclusion about the effect of SPDRs' trading was reached. When taking transaction costs into consideration, it was observed that the frequency and magnitude of violations had dropped dramatically. The dollar size of these violations, however, was still substantial and would require further inspection. Nevertheless, one should not forget that these figures are ex post and that there is no guarantee that those profitable arbitrage opportunities would persist over time.

According to the findings of this study, the effect of SPDRs' trading is more apparent in the index futures market than in the index options market. However, these results may be caused by economic reasons other than the presence of SPDRs in the market. To arrive at a solid conclusion on the effects of SPDRs, one should examine other factors that are attributes of market efficiency such as basis risk, marking-to-market, or trading volume. Also, since the index futures, the index options, and SPDRs, are all based on the same underlying asset, the S&P 500 stock index, it is to be expected that their prices be interrelated with one another and the underlying stock index itself. If prices of the different instruments and/or the index itself do not satisfy the relevant inter-market relationships, the relative mispricing should be instantaneously corrected given efficient markets and the high degree of sophistication of market participants. The price adjustments could be accomplished by a variety of cross-market strategies. For future research, the relationship between, for instance, S&P 500 index futures, index options, and SPDRs should be examined.

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APPENDIX 1: SUMMARY STATISTICS OF DAILY AND INTRADAILY INDEX FUTURES MISPRICING SERIES

Table 1.a: Summary Statistics on the Daily Differences between Actual and Theoretical Futures Prices: Jan. 90 – Jun. 96

	Jan. 90 – Jan. 93	Feb. 93 – Jun. 96	Jan. 90 - Jun. 96
Number of Observations	756[a]	832	1594
Average Mispricing	0.360	0.176[c]	0.264
(x 10^{-3})	(1.326)	(1.257)	(1.293)
t-stat for H0: mean = 0	7.473*	4.057*	8.1374*
Average Absolute Mispricing	1.044	0.988	1.015
(x 10^{-3})	(0.892)	(0.796)	(0.843)
t-stat for H0: mean = 0	32.203*	35.924*	48.0577*
Average days to Maturity	0.142	0.139	0.141
	(0.0726)	(0.0719)	(0.0722)

Standard deviations are in parentheses

* t-stat for mean equal to zero is significant at the 1% level of significance

a The sample includes January 1993.

Table 1.b: Summary Statistics on the Intradaily Differences between Actual and Theoretical Futures Prices: Jan. 90 – Jun. 96

	Jan. 90 – Jan. 93	Feb. 93 – Jun. 96	Jan. 90 - Jun. 96
Number of Observations	5292[a]	5866	11158
Average Mispricing	0.367	0.140[c]	0.248
(x 10^{-3})	(1.285)	(1.183)	(1.237)
t-stat for H0: mean = 0	20.808*	9.072*	21.166*
Average Absolute Mispricing	1.022	0.929	0.973
(x 10^{-3})	(0.861)	(0.746)	(0.804)
t-stat for H0: mean = 0	86.348*	95.349*	127.844*
Average days to Maturity	0.142	0.139	0.141
	(0.0726)	(0.0719)	(0.0722)

Standard deviations are in parentheses

* t-stat for mean equal to zero is significant at the 1% level of significance

a The sample includes January 1993.

Table 2a: Hypotheses Tests for Futures Mispricing Series:

t-stat For Daily Difference In Means (rolled over contracts)

Average Mispricing:

DUM	N	Mean	Std Dev	Std Error	Minimum	Maximum
0	756	0.00036034	0.00132577	0.00004822	-0.00567163	0.01081758
1	838	0.00017620	0.00125706	0.00004342	-0.00678787	0.00352526
Variances	T	DF	Prob>|T|			
Unequal	2.8377	1554.2	0.0046			
Equal	**2.8455**	**1592.0**	**0.0045**			

For H0: Variances are equal, F' = 1.11 DF = (755,837) Prob>F' = 0.1333

Absolute Average Mispricing:

DUM	N	Mean	Std Dev	Std Error	Minimum	Maximum
0	756	0.00104449	0.00089179	0.00003243	4.02780E-06	0.01081758
1	838	0.00098805	0.00079617	0.00002750	8.57744E-07	0.00678787
Variances	T	DF	Prob>|T|			
Unequal	**1.3272**	**1521.5**	**0.1846**			
Equal	1.3350	1592.0	0.1821			

For H0: Variances are equal, F' = 1.25 DF = (755,837) Prob>F' = 0.0014

Average Maturity

DUM	N	Mean	Std Dev	Std Error	Minimum	Maximum
0	756	0.14202025	0.07264910	0.00264222	0.01918000	0.27945000
1	838	0.13952031	0.07195787	0.00248574	0.01918000	0.27945000
Variances	T	DF	Prob>|T|			
Unequal	0.6891	1572.1	0.4908			
Equal	**0.6895**	**1592.0**	**0.4906**			

For H0: Variances are equal, F' = 1.02 DF = (755,837) Prob>F' = 0.7867

t-stat For Intradaily Difference In Means (rolled over futures contracts)

Average Mispricing:

DUM	N	Mean	Std Dev	Std Error	Minimum	Maximum
0	5292	0.00036748	0.00128469	0.00001766	-0.01596300	0.01081800
1	5866	0.00014012	0.00118299	0.00001545	-0.00691500	0.00716400
Variances	T	DF	Prob>|T|			
Unequal	**9.6907**	**10787.4**	**0.0001**			
Equal	9.7318	11156.0	0.0000			

For H0: Variances are equal, F' = 1.18 DF = (5291,5865) Prob>F' = 0.0000

Absolute Average Mispricing:

DUM	N	Mean	Std Dev	Std Error	Minimum	Maximum
0	5292	0.00102185	0.00086088	0.00001183	0	0.01596300
1	5866	0.00092869	0.00074598	0.00000974	0	0.00716400
Variances	T	DF	Prob>|T|			
Unequal	**6.0780**	**10528.6**	**0.0001**			
Equal	6.1227	11156.0	0.0000			

For H0: Variances are equal, F' = 1.33 DF = (5291,5865) Prob>F' = 0.0000

Average Maturity

DUM	N	Mean	Std Dev	Std Error	Minimum	Maximum
0	5292	0.14202284	0.07260636	0.00099808	0.01918000	0.27945000
1	5866	0.13952919	0.07192319	0.00093907	0.01918000	0.27945000
Variances	T	DF	Prob>|T|			
Unequal	1.8196	11016.6	0.0688			
Equal	**1.8205**	**11156.0**	**0.0687**			

For H0: Variances are equal, F' = 1.02 DF = (5291,5865) Prob>F' = 0.4804

Table 1.1: Unit Root Tests for Daily Futures Mispricing Series:

Signed Data:

Unit Root Tests on Daily Futures Mispricing				
	PP	PPT	DF	DFT
Contracts Held Till Maturity	-25.513*	-25.603*	-25.497*	-25.578*
Contracts Rolled Over One Week Before Maturity	-24.240*	-24.303*	-24.225*	-24.280*

Unit Root Tests on First Difference of Daily Futures Mispricing				
	PP	PPT	DF	DFT
Contracts Held Till Maturity	-66.953*	-66.952*	-66.910*	-66.889*
Contracts Rolled Over One Week Before Maturity	-67.593*	-67.593*	-67.550*	-67.529*

Absolute Value:

Unit Root Tests on Daily Futures Mispricing				
	PP	PPT	DF	DFT
Contracts Held Till Maturity	-32.379*	-32.634*	-32.358*	-32.603*
Contracts Rolled Over One Week Before Maturity	-30.805*	-30.987*	-30.786*	-30.958*

Unit Root Tests on First Difference of Daily Futures Mispricing				
	PP	PPT	DF	DFT
Contracts Held Till Maturity	-68.314*	-68.314*	-68.271*	-68.249*
Contracts Rolled Over One Week Before Maturity	-68.301*	-68.301*	-68.258*	-68.237*

PP: Phillips-Perron test statistic for unit root without time trend
PPT: Phillips-Perron test statistic for unit root with time trend
DF: Dickey-Fuller test statistic without time trend
DFT: Dickey-Fuller test statistic with time trend
* Statistic is significant at 1% level

Table 2.1: Q and LM Tests for ARCH Disturbances in Daily Futures Mispricing:

Q and LM Tests for ARCH Disturbances in Daily Futures Mispricing: Jan. 1990 – Jun. 1996

Order	Q	Prob>Q	LM	Prob>LM
1	10.1264	0.0015	10.1258	0.0015
2	17.5359	0.0002	16.2624	0.0003
3	19.4082	0.0002	17.1881	0.0006
4	21.317	0.0003	18.2682	0.0011
5	28.5063	0.0001	23.8286	0.0002
6	28.8436	0.0001	23.8296	0.0006
7	31.0374	0.0001	24.961	0.0008
8	31.1255	0.0001	24.9686	0.0016
9	31.6389	0.0002	25.0658	0.0029
10	33.1156	0.0003	25.7455	0.0041
11	36.6304	0.0001	27.9787	0.0033
12	37.0117	0.0002	27.9787	0.0056

Q and LM Tests for ARCH Disturbances in Intradaily Absolute Values of Futures Mispricing: Jan. 1990 – Jun. 1996

Order	Q	Prob>Q	LM	Prob>LM
1	2.793	0.0947	2.7884	0.0949
2	3.3692	0.1855	3.2647	0.1955
3	3.3899	0.3353	3.2712	0.3517
4	3.5364	0.4724	3.3985	0.4935
5	5.0116	0.4145	4.7796	0.4434
6	5.0776	0.5339	4.9171	0.5545
7	5.0825	0.6499	4.9255	0.669
8	5.0975	0.7471	4.9387	0.7641
9	5.1566	0.8205	4.9759	0.8364
10	5.268	0.8726	5.151	0.8809
11	5.6261	0.8971	5.5123	0.9038
12	5.6829	0.9312	5.5399	0.9375

Sign Bias Tests:

The various sign tests described by GJR and by Engle and Ng (1993) were used to check the specification of the various models.

These tests are as follows:

i) The sign test: a regression of the square of the standardized residuals on a constant and a dummy variable S, that takes the value 1 when the lagged error term is negative, and 0 when this term is positive. The sign bias test is the t statistic of the coefficient of the dummy variable. This test examines the effect of a positive or negative error term from the previous observation on volatility, which has not been captured by the model.

ii) The negative sign bias test is the t statistic of a similar regression run on a constant and the term $S^{-} \varepsilon_{t-1}$. This test considers the effects that large and small negative returns have on the volatility, which were not captured by the model.

iii) The positive sign test is the t statistic of the $S^{+}_{t-1} \varepsilon_{t-1}$ term from the same regression model as above. S^{+}_{t-1} is a dummy variable that is equal to $1 - S^{-}\varepsilon_{t-1}$. This test considers the effects that large and small positive returns have on the volatility, which were not predicted by the model.

Table 3.1: Sign Tests for Daily Futures Mispricing:

1. Futures Mispricing Series for Contracts Held till Maturity: Jan. 1990 – Jan. 1996.

Test	GARCH(1,1)	GJR(1,1)	TGARCH(1,1)
Sign Bias Test	-0.1267	0.0736	0.6284
Negative Sign Bias Test	-0.3651	-0.1794	1.0142
Positive Sign Bias Test	-0.2182	-0.0472	-0.0138
Joint Test	0.9707	0.0361	0.3555
* t statistic is significant at the 1% level of significance			

2. Absolute Value Futures Mispricing Series for Contracts Held till Maturity: Jan. 1990 – Jan. 1996.

Test	GARCH(1,1)	GJR(1,1)	TGARCH(1,1)
Sign Bias Test	0.4529	-4.2078*	0.3635
Negative Sign Bias Test	0.0576	-2.0285	0.0400
Positive Sign Bias Test	0.9301	2.7683	-0.2434
Joint Test	0.2896	11.6238*	0.1727
* t statistic is significant at the 1% level of significance			

Table 4.1: Summary Statistics of Daily Futures Mispricing

Signed Data:

	ARIMA(4,4)	GARCH(1,1)	GJR(1,1)	TGARCH(1,1)
Skewness	0.0344	-0.49170	-0.47066	-1.01451
Kurtosis	9.2538	8.4942	8.07994	16.48864
Q_{20}	17.1541	14.6211	14.5505	17.1569
Q^2_{20}	37.0760*	18.1720	16.6676	5.6645

Absolute Value:

	ARIMA(4,4)	GARCH(1,1)	GJR(1,1)	TGARCH(1,1)
Skewness	2.64139	2.8753	1.44358	3.5594
Kurtosis	21.6347	23.3559	18.8929	35.1625
Q_{20}	5.2841	9.2448	11108.74*	26.4835*
Q^2_{20}	8.7335	3.4248	5.8309	1.3777

Table 1.2: Unit Root Tests for Intradaily Futures Mispricing Series

Signed Data:

Unit Root Tests on Intradaily Futures Mispricing				
	PP	PPT	DF	DFT
Contracts Held Till Maturity	-47.9421*	-48.2860*	-47.937*	-48.279*
Contracts Rolled Over One Week Before Maturity	-46.630*	-46.849*	-46.626*	-46.843*

Unit Root Tests on First Difference of Intradaily Futures Mispricing				
	PP	PPT	DF	DFT
Contracts Held Till Maturity	-167.175*	-167.175*	-167.160*	-167.152*
Contracts Rolled Over One Week Before Maturity	-169.350*	-169.350*	-169.335*	-169.327*

Absolute Value:

Unit Root Tests on Intradaily Futures Mispricing				
	PP	PPT	DF	DFT
Contracts Held Till Maturity	-63.207*	-63.888*	-63.201*	-63.879*
Contracts Rolled Over One Week Before Maturity	-61.249*	-61.751*	-61.2448*	-61.743*

Unit Root Tests on First Difference of Intradaily Futures Mispricing				
	PP	PPT	DF	DFT
Contracts Held Till Maturity	-168.566*	-168.566*	-168.550*	-168.543*
Contracts Rolled Over One Week Before Maturity	-170.795*	-170.795*	-170.779*	-170.772*

PP: Phillips-Perron test statistic for unit root without time trend
PPT: Phillips-Perron test statistic for unit root with time trend
DF: Dickey-Fuller test statistic without time trend
DFT: Dickey-Fuller test statistic with time trend
* statistic is significant at 1% level

Table 2.2: Q and LM Tests for ARCH Disturbances in Intradaily Futures Mispricing

Q and LM Tests for ARCH Disturbances in Intradaily Futures Mispricing: Jan. 1990 – Jun. 1996				
Order	Q	Prob>Q	LM	Prob>LM
1	532.707	0.0001	532.519	0.0001
2	837.898	0.0001	694.084	0.0001
3	1435.92	0.0001	1048.68	0.0001
4	1778.01	0.0001	1129.24	0.0001
5	2100.29	0.0001	1202.59	0.0001
6	2328.75	0.0001	1220.4	0.0001
7	2437.08	0.0001	1220.41	0.0001
8	2535.46	0.0001	1220.86	0.0001
9	2628.52	0.0001	1222.76	0.0001
10	2698.71	0.0001	1224.34	0.0001
11	2793.58	0.0001	1236.36	0.0001
12	2874.65	0.0001	1243.48	0.0001

Q and LM Tests for ARCH Disturbances in Intradaily Absolute Values of Futures Mispricing: Jan. 1990 – Jun. 1996				
Order	Q	Prob>Q	LM	Prob>LM
1	147.825	0.0001	147.784	0.0001
2	216.63	0.0001	195.853	0.0001
3	433.999	0.0001	368.869	0.0001
4	543.406	0.0001	419.806	0.0001
5	662.112	0.0001	476.505	0.0001
6	754.198	0.0001	503.93	0.0001
7	769.569	0.0001	504.194	0.0001
8	783.336	0.0001	504.232	0.0001
9	793.375	0.0001	504.421	0.0001
10	800.158	0.0001	504.422	0.0001
11	813.153	0.0001	506.76	0.0001
12	820.402	0.0001	507.712	0.0001

Table 3.2: Sign Tests for Intradaily Futures Mispricing Series

1. Futures Mispricing Series for Contracts Held till Maturity: Jan. 1990 – Jan. 1996.

Test	GARCH(1,1)	GJR(1,1)	TGARCH(1,1)
Sign Bias Test	-2.6208*	-1.1418	0.1609
Negative Sign Bias Test	-20.2721*	-0.4202	-0.6754
Positive Sign Bias Test	9.3185*	-0.3513	0.0003
Joint Test	168.9770*	0.4927	0.3156

* t statistic is significant at the 1% level of significance

2. Futures Mispricing Series for Contracts Rolled over One Week before Maturity: Jan. 1990 – Jan. 1996.

Test	GARCH(1,1)	GJR(1,1)	TGARCH(1,1)
Sign Bias Test	0.6288	1.0651	4.7909*
Negative Sign Bias Test	-0.7022	0.0556	0.1962
Positive Sign Bias Test	0.7249	1.1313	-0.9740
Joint Test	0.5763	0.5596	26.136*

* t statistic is significant at the 1% level of significance

Table 4.2: Summary Statistics of Intradaily Futures Mispricing Series

Contracts Held Till Maturity:

	ARIMA(4,4)	GARCH(1,1)	GJR(1,1)	TGARCH(1,1)
Skewness	-0.79358	-0.74503	-0.73851	-0.93991
Kurtosis	15.62224	9.98537	15.22343	10.12769
Q_{20}	18.3652	2220.6042*	28.1609	0.7085
Q^2_{20}	644.5493*	5894.0785*	2.6109	1.7377e-003

Contracts Rolled Over One Week before Maturity:

	ARIMA(4,4)	GARCH(1,1)	GJR(1,1)	TGARCH(1,1)
Skewness	-0.78346		-0.73736	-0.12111
Kurtosis	15.67992		15.44255	1.00335
Q_{20}	23.9137*		29.7342*	
Q^2_{20}	668.3458*		31.0426*	

APPENDIX 2: RESULTS OF MODELS FITTED ON DAILY FUTURES MISPRICING

A. Models for Daily Futures Mispricing

1. ARIMA(4,0,4) Model :

$$x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

Where,

α_0 = constant term,
ϕ_i = ith autoregressive parameter,
θ_j = jth moving average parameter,
ε_t = the error term at time t

Estimates of ARIMA(4,4) Model for Daily Futures Mispricing
Jan 1990-Jun. 1996

Variable	Coeff.	Std Error	T-Stat	P-Value
α_0	0.000308	0.000159	1.93179	0.053565
ϕ_1	0.464005	0.285375	1.62595	0.104161
ϕ_2	-0.20872	0.327571	-0.63717	0.524106
ϕ_3	-0.06407	0.317052	-0.20208	0.839877
ϕ_4	0.607604	0.241758	2.51328	0.012061
θ_1	-0.24559	0.290334	-0.84588	0.397746
θ_2	0.337086	0.273397	1.23295	0.217779
θ_3	0.189225	0.3119	0.60669	0.544147
θ_4	-0.45174	0.194197	-2.32619	0.020135
α_1	-0.00018	0.000215	-0.82855	0.407485
	Log Likelihood			10003.45
	Number of Observations			1584

2. ARIMA(4,0,4)-GARCH(1,1) Model :

$$x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, h_t)$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}$$

Estimates of ARIMA(4,4)-GARCH(1,1) Model for Daily Futures Mispricing: Jan. 1990 - Jun. 1996)

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	5.78E-06	4.18E-06	1.38284	0.1667
ϕ_1	2.072	8.63E-02	24.01634	0.0000
ϕ_2	-2.214	0.119	-18.6622	0.0000
ϕ_3	1.731	0.139	12.44041	0.0000
ϕ_4	-0.605	9.13E-02	-6.62865	0.0000
θ_1	-1.804	9.76E-02	-18.4909	0.0000
θ_2	1.882	0.123	15.35099	0.0000
θ_3	-1.399	0.143	-9.76189	0.0000
θ_4	0.402	8.20E-02	4.90697	0.0000
α_1	-2.17E-06	4.17E-06	-0.5203	0.6029
β_0	8.14E-09	2.05E-09	3.97143	0.0001
β_1	3.20E-02	4.43E-03	7.23842	0.0000
β_2	0.961	4.67E-03	206.0698	0.0000
	Log Likelihood			10067.09
	Number of Observations			1584

3. ARIMA(4,0,4)-GJR(1,1) Model :

$$x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, h_t)$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 s_{t-1}^- \varepsilon_{t-1}^2 + \beta_3 h_{t-1}$$

Estimates of ARIMA(4,4)-GJR(1,1) Model for Daily Futures Mispricing
Jan. 1990 - Jun. 1996

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	5.87E-06	4.25E-06	1.38176	0.1670
ϕ_1	2.076	8.51E-02	24.38362	0.0000
ϕ_2	-2.221	0.117	-18.9284	0.0000
ϕ_3	1.736	0.137	12.64807	0.0000
ϕ_4	-0.606	8.94E-02	-6.78435	0.0000
θ_1	-1.808	9.62E-02	-18.8009	0.0000
θ_2	1.889	0.121	15.63282	0.0000
θ_3	-1.402	0.141	-9.94699	0.0000
θ_4	0.403	8.01E-02	5.03032	0.0000
α_1	-2.30E-06	4.14E-06	-0.55572	0.5784
β_0	8.35E-09	2.13E-09	3.9274	0.0001
β_1	2.59E-02	5.27E-03	4.91954	0.0000
β_2	0.962	4.83E-03	199.2133	0.0000
β_3	1.00E-02	9.13E-03	1.09709	0.2726
	Log-Likelihood			10067.38
	Number of Observations			1584

4. ARIMA(4,0,4)-TGARCH(1,1) Model

$$x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\varepsilon_t | \psi_{t-1} \sim f_v(\varepsilon_t | \psi_{t-1})$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}$$

Estimates of ARIMA(4,4)-TGARCH(1,1) Model for Daily Futures Mispricing: Jan. 1990-Jun. 1996)

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	7.25E-05	3.51E-05	2.06488	0.0389
ϕ_1	0.425	0.13	3.27855	0.0010
ϕ_2	-8.19E-02	0.163	-0.50373	0.6145
ϕ_3	-0.285	0.151	-1.88828	0.0590
ϕ_4	0.733	0.107	6.84263	0.0000
θ_1	-0.174	0.138	-1.26394	0.2063
θ_2	0.234	0.145	1.60938	0.1075
θ_3	0.409	0.147	2.78371	0.0054
θ_4	-0.497	8.82E-02	-5.63672	0.0000
α_1	-1.71E-05	4.37E-05	-0.38973	0.6967
β_0	1.78E-08	7.71E-09	2.31564	0.0206
β_1	3.07E-02	9.03E-03	3.39893	0.0007
β_2	0.952	1.37E-02	69.39854	0.0000
d	5.776	0.661	8.73946	0.0000
	Log Likelihood			19903
	Number of Observations			1584

B. Models for Daily Futures |Mispricing|

1. ARIMA(4,0,4) Model :

$$|x_t| = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

Estimates of ARIMA(4,4) Model for Daily Futures Mispricing
Jan 1990-Jun. 1996

Variable	Coeff.	Std Error	T-Stat	P-Value
α_0	0.000991	6.47E-05	15.31543	0.0000
ϕ_1	-0.28303	0.340479	-0.83126	0.4060
ϕ_2	1.121931	0.226732	4.94826	0.0000
ϕ_3	0.340921	0.251063	1.35791	0.1747
ϕ_4	-0.33259	0.203601	-1.63352	0.1026
θ_1	0.442836	0.345389	1.28214	0.2000
θ_2	-0.9478	0.27482	-3.44881	0.0006
θ_3	-0.3928	0.194784	-2.01661	0.0439
θ_4	0.23823	0.183486	1.29835	0.1944
α_1	-4.6E-05	8.82E-05	-0.52064	0.6027
	Log Likelihood			18874
	Number of Observations			1584

2. ARIMA(4,0,4)-GARCH(1,1) Model :

$$|x_t| = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, h_t)$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}$$

Estimates of ARIMA(4,4)-GARCH(1,1) Model for Daily Futures Mispricing: Jan. 1990 - Jun. 1996)

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	5.37E-06	6.23E-06	0.86107	0.3892
ϕ_1	0.104	0.119	0.8748	0.3817
ϕ_2	1.295	0.121	10.73142	0.0000
ϕ_3	0.147	9.42E-02	1.56326	0.1180
ϕ_4	-0.552	8.81E-02	-6.26717	0.0000
θ_1	5.31E-02	0.126	0.42061	0.6740
θ_2	-1.15	0.122	-9.41301	0.0000
θ_3	-0.264	9.92E-02	-2.65935	0.0078
θ_4	0.391	9.39E-02	4.15964	0.0000
α_1	2.31E-07	1.14E-06	0.20254	0.8395
β_0	4.30E-09	1.41E-09	3.03993	0.0024
β_1	3.84E-02	6.86E-03	5.59728	0.0000
β_2	0.957	6.38E-03	150.119	0.0000
	Log Likelihood			10538.07
	Number of Observations			1584

3. ARIMA(4,0,4)-GJR(1,1) Model :

$$|x_t| = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, h_t)$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 s_{t-1}^- \varepsilon_{t-1}^2 + \beta_3 h_{t-1}$$

Estimates of ARIMA(4,4)-GJR(1,1) Model for Daily Futures Mispricing
Jan. 1990 - Jun. 1996

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	-3.25E-05	4.95E-07	-65.7765	0.0000
ϕ_1	-1.711	9.11E-07	-1877398	0.0000
ϕ_2	9.12E-02	3.38E-05	2699.851	0.0000
ϕ_3	1.735	1.22E-06	1426813	0.0000
ϕ_4	0.905	8.21E-07	1101368	0.0000
θ_1	1.75	2.04E-06	857564.2	0.0000
θ_2	-2.47E-02	1.55E-05	-1598.48	0.0000
θ_3	-1.728	4.04E-06	-427347	0.0000
θ_4	-0.922	5.25E-06	-175673	0.0000
α_1	1.60E-05	1.54E-06	10.38605	0.0000
β_0	2.62E-08	7.53E-09	3.47848	0.0005
β_1	9.62E-02	1.41E-02	6.82952	0.0000
β_2	0.816	2.57E-02	31.78021	0.0000
β_3	0.259	3.08E-02	8.38582	0.0000
	Log-Likelihood			10488.62
	Number of Observations			1584

4. ARIMA(4,0,4)-TGARCH(1,1) Model

$$|x_t| = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\varepsilon_t | \psi_{t-1} \sim f_v(\varepsilon_t | \psi_{t-1})$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}$$

Estimates of ARIMA(4,4)-TGARCH(1,1) Model for Daily Futures Mispricing: Jan. 1990-Jun 1996)

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	0.000494	0.000187	2.64644	0.0081
ϕ_1	-1.23848	0.364524	-3.39752	0.0007
ϕ_2	0.386551	0.412319	0.9375	0.3485
ϕ_3	0.931103	0.27971	3.32882	0.0009
ϕ_4	0.291342	0.316298	0.9211	0.3570
θ_1	1.399804	0.363121	3.85492	0.0001
θ_2	-0.03851	0.465747	-0.08268	0.9341
θ_3	-0.70828	0.181823	-3.89546	0.0001
θ_4	-0.25684	0.256452	-1.0015	0.3166
α_1	-4E-05	4.33E-05	-0.92178	0.3566
β_0	5.1E-08	1.5E-08	3.51407	0.0004
β_1	0.099235	0.026438	3.75355	0.0002
β_2	0.80794	0.040177	20.10949	0.0000
d	5.188971	0.438757	11.82652	0.0000
	Log Likelihood			10137.11
	Number of Observations			1584

APPENDIX 3: RESULTS OF MODELS FITTED ON INTRADAILY FUTURES MISPRICING SERIES

1. ARIMA(4,0,4) Model :

$$x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

Where.

α_0 = constant term,
ϕ_i = ith autoregressive parameter,
θ_j = jth moving average parameter,
ε_t = the error term at time t.

Estimates of ARIMA(4,4) Model for Futures Mispricing Contracts Held Till Maturity: Jan 1990-Jun. 1996

Variable	Coeff.	Std Error	T-Stat	P-Value
α_0	0.0003005	0.0001495	2.01063	0.0444
ϕ_1	0.6926395	0.1724401	4.0167	0.0001
ϕ_2	0.4140275	0.2051035	2.01863	0.0436
ϕ_3	0.1590905	0.1950653	0.81558	0.4148
ϕ_4	-0.2764756	0.1210429	-2.28411	0.0224
θ_1	-0.3659653	0.173422	-2.11026	0.0349
θ_2	-0.3707546	0.1629785	-2.27487	0.0229
θ_3	-0.2277399	0.1740368	-1.30857	0.1907
θ_4	0.1101962	0.079825	1.38047	0.1675
α_1	-0.0002111	0.000198	-1.06594	0.2865
	Log Likelihood			73148.475
	Number of Observations			11088

2. ARIMA(4,0,4)-GARCH(1,1) Model :

$$x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, h_t)$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 dumo_t + \beta_4 dumc_t + \beta_5 dumw$$

Estimates of ARIMA(4,4)-GARCH(1,1) Model for Futures Mispricing Contracts Held Till Maturity: Jan. 1990 - Jun. 1996

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	3.66E-04	7.12E-05	5.13707	0.0000
ϕ_1	3.64E-02	0.153	0.23814	0.8118
ϕ_2	-0.249	3.62E-02	-6.87997	0.0000
ϕ_3	0.949	4.29E-02	22.1274	0.0000
ϕ_4	0.147	0.155	0.94922	0.3425
θ_1	0.212	0.141	1.50042	0.1335
θ_2	0.439	3.25E-02	13.52091	0.0000
θ_3	-0.655	6.12E-02	-10.69795	0.0000
θ_4	-0.132	0.115	-1.14393	0.2527
α_1	-3.43E-04	5.42E-04	-0.63174	0.5276
β_0	3.32E-07	9.29E-08	3.57217	0.0004
β_1	-6.19E-02	4.93E-03	-12.55621	0.0000
β_2	0.726	1.73E-02	41.92653	0.0000
β_3	4.55E-06	5.02E-07	9.06594	0.0000
β_4	2.39E-06	3.23E-07	7.39412	0.0000
β_5	4.29E-06	3.72E-07	11.52169	0.0000
	Log Likelihood			60694.699
	Number of Observations			11088

3. ARIMA(4,0,4)-GJR(1,1) Model :

$$x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, h_t)$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 s_{t-1}^- \varepsilon_{t-1}^2 + \beta_3 h_{t-1} + \beta_4 dumo_t + \beta_5 dumc_t + \beta_6 dumw$$

Estimates of ARIMA(4,4)-GJR(1,1) Model for Futures Mispricing
Contracts Held Till Maturity: Jan. 1990 - Jun. 1996

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	8.16E-06	2.39E-06	3.41809	0.0006
ϕ_1	0.799	4.26E-02	18.73555	0.0000
ϕ_2	-0.297	7.41E-03	-40.06729	0.0000
ϕ_3	1.104	8.57E-03	128.83011	0.0000
ϕ_4	-0.619	4.18E-02	-14.80162	0.0000
θ_1	-0.436	4.59E-02	-9.49686	0.0000
θ_2	0.307	4.89E-03	62.64754	0.0000
θ_3	-0.976	1.77E-02	-55.28914	0.0000
θ_4	0.331	3.49E-02	9.48176	0.0000
α_1	-5.35E-06	2.48E-06	-2.15678	0.0310
β_0	-2.96E-08	8.57E-10	-34.50101	0.0000
β_1	2.66E-02	2.22E-03	11.96408	0.0000
β_2	0.936	2.12E-03	441.69699	0.0000
β_3	5.21E-02	3.31E-03	15.77059	0.0000
β_4	6.35E-08	5.10E-09	12.44419	0.0000
β_5	2.07E-07	5.23E-09	39.55486	0.0000
β_6	1.79E-10	2.23E-09	0.08045	0.9359
	Log-Likelihood			73725.706
	Number of Observations			11088

4. ARIMA(4,0,4)-TGARCH(1,1) Model

$$x_t = \alpha_0 + \alpha_1 dum_t + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=1}^{4} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\varepsilon_t | \psi_{t-1} \sim f_v(\varepsilon_t | \psi_{t-1})$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 dumo_t + \beta_4 dumc_t + \beta_5 dumw$$

Estimates of ARIMA(4,4)-TGARCH(1,1) Model for Futures Mispricing Contracts Held Till Maturity: Jan. 1990-Jun 1996

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	5.41E-04	9.63E-05	5.61812	0.0000
ϕ_1	-2.92E-02	0.152	-0.19208	0.8477
ϕ_2	8.86E-02	2.35E-02	3.76612	0.0002
ϕ_3	0.959	1.74E-02	55.25633	0.0000
ϕ_4	-8.84E-02	0.149	-0.59393	0.5526
θ_1	0.228	0.162	1.41073	0.1583
θ_2	8.72E-02	5.01E-02	1.74099	0.0817
θ_3	-0.759	2.57E-02	-29.51536	0.0000
θ_4	3.87E-02	0.126	0.30833	0.7578
α_1	-5.15E-04	1.27E-04	-4.05546	0.0001
β_0	-5.63E-09	3.06E-09	-1.83675	0.0662
β_1	-1.87E-02	1.37E-03	-13.63261	0.0000
β_2	0.753	6.99E-03	107.65707	0.0000
β_3	2.45E-06	2.20E-07	11.12833	0.0000
β_4	2.59E-06	2.54E-07	10.18651	0.0000
β_5	1.32E-06	1.42E-07	9.26919	0.0000
d	8.104	0.918	8.82604	0.0000
	Log Likelihood			61516.701
	Number of Observations			11088

APPENDIX 4: RESULTS FOR DAILY MISPRICING SERIES USING CONTRACTS ROLLED OVER ONE WEEK BEFORE EXPIRATION

1. Q and LM Tests for ARCH Disturbances in Daily Futures Mispricing:

Q and LM Tests for ARCH Disturbances in Intradaily Futures Mispricing: Jan. 1990 – Jun. 1996

Order	Q	Prob>Q	LM	Prob>LM
1	13.9759	0.0002	13.9695	0.0002
2	24.8163	0.0001	22.711	0.0001
3	28.3857	0.0001	24.4707	0.0001
4	32.3103	0.0001	26.6233	0.0001
5	43.3701	0.0001	34.4913	0.0001
6	44.5685	0.0001	34.5693	0.0001
7	46.4627	0.0001	35.063	0.0001
8	46.8559	0.0001	35.0703	0.0001
9	47.9596	0.0001	35.3034	0.0001
10	49.0865	0.0001	35.5272	0.0001
11	53.4516	0.0001	38.105	0.0001
12	53.9882	0.0001	38.1064	0.0001

Q and LM Tests for ARCH Disturbances in Intradaily Absolute Values of Futures Mispricing: Jan. 1990 – Jun. 1996

Order	Q	Prob>Q	LM	Prob>LM
1	3.3557	0.067	3.3516	0.0671
2	4.0206	0.1339	3.8892	0.143
3	4.1074	0.2501	3.9381	0.2682
4	4.3875	0.3561	4.1763	0.3827
5	5.9751	0.3086	5.6172	0.3453
6	5.9751	0.426	5.6337	0.4654
7	6.0248	0.5369	5.7075	0.5743
8	6.0453	0.6422	5.729	0.6776
9	6.1632	0.7235	5.7999	0.7598
10	6.2896	0.7904	6.0147	0.814
11	6.5654	0.8331	6.2817	0.8539
12	6.5883	0.8836	6.2896	0.9008

2. Summary Statistics of Daily Futures Mispricing

Signed Data:

	ARIMA(4,4)	GARCH(1,1)	GJR(1,1)	TGARCH(1,1)
Skewness	0.01130	-0.41103	0.01238	-0.77986
Kurtosis	9.23564	7.82128	9.26107	12.35361
Q_{20}	33.4752*	27.7010*	32.1070*	26.3980*
Q^2_{20}	38.4423*	33.3082*	39.5158*	9.2573

Absolute Value:

	ARIMA(4,4)	GARCH(1,1)	GJR(1,1)	TGARCH(1,1)
Skewness	2.56346	4.41195	-0.10853	3.42156
Kurtosis	21.64323	59.3203	-0.99356	34.7501
Q_{20}	8.9923	69.696*	1409.709*	96.9801*
Q^2_{20}	7.6558	6.2007	3471.593*	1.3583*

3. Sign Tests:

3.1. Signed Data

Test	GARCH(1,1)	GJR(1,1)	TGARCH(1,1)
Sign Bias Test	-1.3288	-1.2710	-0.6942
Negative Sign Bias Test	-1.3514	-1.1859	0.5048
Positive Sign Bias Test	-0.5821	-0.3608	-0.8108
Joint Test	0.8024	0.6728	0.4894
* t statistic is significant at the 1% level of significance			

3.2. Absolute Value

Test	GARCH(1,1)	GJR(1,1)	TGARCH(1,1)
Sign Bias Test	0.3357	-0.3983	0.6063
Negative Sign Bias Test	-1.3581	-2.9159*	-0.1548
Positive Sign Bias Test	1.9242	3.5328*	0.0024
Joint Test	1.8490	7.1597*	0.3076
* t statistic is significant at the 1% level of significance			

4.1 ARIMA(4,0,4) Model:

Estimates of ARIMA(4,4) Model for Daily Futures Mispricing
Jan 1990-Jun. 1996

Variable	Coeff.	Std Error	T-Stat	P-Value
α_0	0.000352	0.000178	1.97736	0.0482
ϕ_1	0.560812	0.375801	1.49231	0.1358
ϕ_2	-0.31696	0.44171	-0.71758	0.4731
ϕ_3	0.032414	0.428845	0.07558	0.9398
ϕ_4	0.546113	0.322382	1.69399	0.0905
θ_1	-0.32248	0.380178	-0.84823	0.3964
θ_2	0.427863	0.35798	1.19521	0.2322
θ_3	0.112411	0.414433	0.27124	0.7862
θ_4	-0.39215	0.247707	-1.58311	0.1136
α_1	-0.00017	0.000238	-0.71672	0.4737
	Log Likelihood			10077.33
	Number of Observations			1594

Estimates of ARIMA(4,4) Model for Daily Futures |Mispricing|
Jan 1990-Jun. 1996

Variable	Coeff.	Std Error	T-Stat	P-Value
α_0	0.001035	6.85E-05	15.12409	0.0000
ϕ_1	-1.02433	0.241232	-4.24626	0.0000
ϕ_2	0.609138	0.186127	3.2727	0.0011
ϕ_3	0.825153	0.174006	4.7421	0.0000
ϕ_4	0.07179	0.157221	0.45662	0.6480
θ_1	1.207018	0.242784	4.97158	0.0000
θ_2	-0.27039	0.233245	-1.15926	0.2465
θ_3	-0.64652	0.124806	-5.18023	0.0000
θ_4	-0.06078	0.131744	-0.46135	0.6446
α_1	-4.6E-05	9.35E-05	-0.49275	0.6223
	Log Likelihood			10545.37
	Number of Observations			1594

4.2 ARIMA(4,0,4)-GARCH(1,1) Model:

Estimates of ARIMA(4,4)-GARCH(1,1) Model for Daily Futures Mispricing: Jan. 1990 - Jun. 1996)

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	1.78E-06	1.27E-06	1.39993	0.1615
ϕ_1	2.161	4.50E-02	48.04298	0.0000
ϕ_2	-2.302	9.14E-02	-25.1908	0.0000
ϕ_3	1.899	9.98E-02	19.02714	0.0000
ϕ_4	-0.761	4.97E-02	-15.3087	0.0000
θ_1	-1.881	5.56E-02	-33.8546	0.0000
θ_2	1.958	9.40E-02	20.82581	0.0000
θ_3	-1.596	9.42E-02	-16.9421	0.0000
θ_4	0.543	4.76E-02	11.41522	0.0000
α_1	-7.98E-07	1.21E-06	-0.65942	0.5096
β_0	8.25E-09	2.17E-09	3.81043	0.0001
β_1	3.63E-02	4.93E-03	7.37296	0.0000
β_2	0.957	4.79E-03	199.6428	0.0000
	Log Likelihood			10146.22
	Number of Observations			1594

Estimates of ARIMA(4,4)-GARCH(1,1) Model for Daily Futures |Mispricing| : Jan. 1990 - Jun. 1996)

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	7.71E-04	1.50E-04	5.15055	0.0000
ϕ_1	-1.882	6.53E-02	-28.8104	0.0000
ϕ_2	-0.143	7.90E-02	-1.8158	0.0694
ϕ_3	1.529	6.79E-02	22.52846	0.0000
ϕ_4	0.779	5.53E-02	14.08656	0.0000
θ_1	2.085	6.94E-02	30.03883	0.0000
θ_2	0.677	0.111	6.12531	0.0000
θ_3	-1.049	9.16E-02	-11.4473	0.0000
θ_4	-0.63	5.51E-02	-11.4234	0.0000
α_1	-8.99E-05	3.43E-05	-2.61821	0.0088
β_0	4.23E-09	1.49E-09	2.83325	0.0046
β_1	4.61E-02	7.12E-03	6.47506	0.0000
β_2	0.951	5.46E-03	174.3604	0.0000
	Log Likelihood			10602.8
	Number of Observations			1594

4.3 ARIMA(4,0,4)-GJR(1,1) Model:

Estimates of ARIMA(4,4)-GJR(1,1) Model for Daily Futures Mispricing
Jan. 1990 - Jun. 1996

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	1.77E-06	1.25E-06	1.4207	0.1554
ϕ_1	2.16	4.58E-02	47.15197	0.0000
ϕ_2	-2.297	9.52E-02	-24.1275	0.0000
ϕ_3	1.89	0.103	18.30565	0.0000
ϕ_4	-0.757	5.06E-02	-14.9737	0.0000
θ_1	-1.878	5.61E-02	-33.5006	0.0000
θ_2	1.95	9.72E-02	20.06335	0.0000
θ_3	-1.585	9.70E-02	-16.3489	0.0000
θ_4	0.538	4.81E-02	11.17279	0.0000
α_1	-8.42E-07	1.19E-06	-0.71008	0.4777
β_0	8.51E-09	2.23E-09	3.82477	0.0001
β_1	2.70E-02	6.71E-03	4.02499	0.0001
β_2	0.958	4.91E-03	195.166	0.0000
β_3	1.47E-02	1.09E-02	1.34808	0.1776
	Log-Likelihood			10146.74
	Number of Observations			1594

Estimates of ARIMA(4,4)-GJR(1,1) Model for Daily Futures |Mispricing| :Jan. 1990 - Jun. 1996

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	2.56E-04	2.31E-05	11.11665	0.0000
ϕ_1	-1.745	5.89E-03	-296.297	0.0000
ϕ_2	3.44E-02	7.07E-03	4.86694	0.0000
ϕ_3	1.663	8.51E-04	1955.327	0.0000
ϕ_4	0.847	3.33E-03	254.4402	0.0000
θ_1	1.86	5.01E-03	371.2582	0.0000
θ_2	0.248	2.26E-03	109.4486	0.0000
θ_3	-1.421	9.86E-03	-144.15	0.0000
θ_4	-0.774	8.22E-03	-94.0983	0.0000
α_1	1.63E-06	1.68E-05	0.09702	0.9227
β_0	-9.96E-09	2.22E-09	-4.4831	0.0000
β_1	4.04E-02	7.09E-03	5.69248	0.0000
β_2	0.952	7.53E-03	126.5156	0.0000
β_3	0.118	2.56E-02	4.62509	0.0000
	Log-Likelihood			10528.13
	Number of Observations			1594

4.4 ARIMA(4,0,4)-TGARCH(1,1) Model:

Estimates of ARIMA(4,4)-TGARCH(1,1) Model for Daily Futures Mispricing: Jan. 1990-Jun 1996)

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	5.94E-05	3.47E-05	1.71385	0.0866
ϕ_1	0.932	0.558	1.67029	0.0949
ϕ_2	-0.715	0.712	-1.00505	0.3149
ϕ_3	0.328	0.667	0.4911	0.6234
ϕ_4	0.315	0.461	0.68369	0.4942
θ_1	-0.659	0.562	-1.1733	0.2407
θ_2	0.746	0.562	1.3274	0.1844
θ_3	-0.151	0.618	-0.24508	0.8064
θ_4	-0.184	0.327	-0.56303	0.5734
α_1	-1.30E-05	3.38E-05	-0.38312	0.7016
β_0	1.88E-08	7.96E-09	2.35773	0.0184
β_1	3.55E-02	1.01E-02	3.53466	0.0004
β_2	0.946	1.47E-02	64.28229	0.0000
d	6.231	0.745	8.36525	0.0000
	Log Likelihood			9660.165
	Number of Observations			1594

Estimates of ARIMA(4,4)-TGARCH(1,1) Model for Daily Futures |Mispricing| : Jan. 1990-Jun 1996

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	0.000622	0.000151	4.11025	0.0000
ϕ_1	-1.64311	0.230608	-7.12512	0.0000
ϕ_2	0.038533	0.248544	0.15503	0.8768
ϕ_3	1.26923	0.195394	6.49574	0.0000
ϕ_4	0.580684	0.197631	2.93822	0.0033
θ_1	1.829048	0.231331	7.90663	0.0000
θ_2	0.442747	0.294823	1.50174	0.1332
θ_3	-0.85086	0.137915	-6.16944	0.0000
θ_4	-0.45944	0.157516	-2.91675	0.0035
α_1	-6.3E-05	4.57E-05	-1.3741	0.1694
β_0	4.4E-08	1.3E-08	3.50035	0.0005
β_1	0.105936	0.0266	3.98249	0.0001
β_2	0.815526	0.036903	22.09929	0.0000
d	5.646528	0.486902	11.59684	0.0000
	Log Likelihood			10186.91
	Number of Observations			1594

APPENDIX 5: RESULTS FOR INTRADAILY MISPRICING SERIES USING CONTRACTS ROLLED OVER ONE WEEK BEFORE EXPIRATION

1. Q and LM Tests for ARCH Disturbances in Intradaily Futures Mispricing

Q and LM Tests for ARCH Disturbances in Intradaily Futures Mispricing: Jan. 1990 – Jun. 1996

Order	Q	Prob>Q	LM	Prob>LM
1	618.905	0.0001	618.698	0.0001
2	1006.12	0.0001	820.605	0.0001
3	1713.81	0.0001	1216.63	0.0001
4	2144.25	0.0001	1312.58	0.0001
5	2537.57	0.0001	1389.58	0.0001
6	2855.48	0.0001	1417.72	0.0001
7	3021.01	0.0001	1418.05	0.0001
8	3169.33	0.0001	1419.09	0.0001
9	3310.84	0.0001	1421.69	0.0001
10	3429.54	0.0001	1425.12	0.0001
11	3565.98	0.0001	1436.65	0.0001
12	3685.77	0.0001	1444.14	0.0001

Q and LM Tests for ARCH Disturbances in Intradaily Absolute Values of Futures Mispricing: Jan. 1990 – Jun. 1996

Order	Q	Prob>Q	LM	Prob>LM
1	172.309	0.0001	172.264	0.0001
2	263.654	0.0001	236.002	0.0001
3	519.838	0.0001	433.449	0.0001
4	666.548	0.0001	501.483	0.0001
5	807.785	0.0001	561.836	0.0001
6	941.771	0.0001	603.986	0.0001
7	973.662	0.0001	604.024	0.0001
8	999.988	0.0001	604.082	0.0001
9	1020.41	0.0001	604.117	0.0001
10	1039.08	0.0001	604.581	0.0001
11	1061.63	0.0001	607.179	0.0001
12	1075.82	0.0001	608.258	0.0001

2. Models:

Estimates of ARIMA(4,4) Model for Intradaily Futures Mispricing

Variable	Coeff.	Std Error	T-Stat	P-Value
α_0	0.000323	0.00017	1.89546	0.0581
ϕ_1	0.760164	0.17235	4.41057	0.0000
ϕ_2	0.376888	0.21142	1.78265	0.0747
ϕ_3	0.112225	0.202729	0.55357	0.5799
ϕ_4	-0.25759	0.12484	-2.06335	0.0391
θ_1	-0.44436	0.173313	-2.56395	0.0104
θ_2	-0.34857	0.170211	-2.04787	0.0406
θ_3	-0.179	0.180082	-0.994	0.3202
θ_4	0.102207	0.083576	1.22293	0.2214
α_1	-0.00017	0.000222	-0.78413	0.4330
	Log Likelihood			73409.699
	Number of Observations			11158

Estimates of ARIMA(4,4)-GARCH(1,1) Model for Futures Mispricing

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	3.44E-06	1.93E-06	1.78556	0.0742
ϕ_1	0.538	3.89E-02	13.85239	0.0000
ϕ_2	0.238	1.56E-02	15.24951	0.0000
ϕ_3	0.877	1.62E-02	54.12171	0.0000
ϕ_4	-0.663	3.79E-02	-17.4913	0.0000
θ_1	-0.208	4.25E-02	-4.90088	0.0000
θ_2	-0.138	1.93E-02	-7.14672	0.0000
θ_3	-0.864	1.58E-02	-54.8394	0.0000
θ_4	0.383	3.38E-02	11.33407	0.0000
α_1	-2.05E-06	2.29E-06	-0.89507	0.3707
β_0	-7.31E-09	1.66E-09	-4.39896	0.0000
β_1	5.92E-02	2.19E-03	27.01488	0.0000
β_2	0.928	2.82E-03	329.5084	0.0000
β_3	3.17E-08	1.17E-08	2.71702	0.0066
β_4	9.93E-08	6.47E-09	15.35982	0.0000
β_5	-1.10E-08	3.21E-09	-3.43468	0.0006
	Log Likelihood			74630.77
	Number of Observations			11158

Estimates of ARIMA(4,4)-GJR(1,1) Model for Futures Mispricing

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	3.77E-06	1.87E-06	2.01098	0.0443
ϕ_1	0.714	3.80E-02	18.77387	0.0000
ϕ_2	-6.92E-02	2.61E-03	-26.4699	0.0000
ϕ_3	1.02	3.14E-03	324.8817	0.0000
ϕ_4	-0.674	3.75E-02	-17.9745	0.0000
θ_1	-0.382	4.17E-02	-9.17027	0.0000
θ_2	0.11	7.48E-03	14.65726	0.0000
θ_3	-0.957	1.03E-02	-92.6188	0.0000
θ_4	0.394	3.36E-02	11.72164	0.0000
α_1	-3.75E-06	2.25E-06	-1.66484	0.0959
β_0	-5.76E-09	1.71E-09	-3.37872	0.0007
β_1	4.95E-02	3.89E-03	12.72962	0.0000
β_2	0.923	3.15E-03	293.6044	0.0000
β_3	2.33E-02	4.29E-03	5.42323	0.0000
β_4	2.79E-08	1.22E-08	2.29011	0.0220
β_5	1.02E-07	6.57E-09	15.46257	0.0000
β_6	-1.02E-08	3.24E-09	-3.14345	0.0017
	Log Likelihood			74637.007
	Number of Observations			11158

Estimates of ARIMA(4,4)-TGARCH(1,1) Model for Futures Mispricing

Variable	Coeff	Std Error	T-Stat	P-Value
α_0	2.80E-04	7.57E-05	3.69232	0.0002
ϕ_1	0.492	6.75E-02	7.29515	0.0000
ϕ_2	0.307	1.51E-02	20.38431	0.0000
ϕ_3	0.909	1.20E-02	75.81915	0.0000
ϕ_4	-0.718	6.96E-02	-10.3127	0.0000
θ_1	-0.215	8.34E-02	-2.57617	0.0100
θ_2	-0.207	2.29E-02	-9.0468	0.0000
θ_3	-0.881	1.30E-02	-67.6402	0.0000
θ_4	0.434	7.77E-02	5.58427	0.0000
α_1	-1.54E-04	1.01E-04	-1.52999	0.1260
β_0	1.84E-07	6.22E-08	2.95259	0.0032
β_1	-6.07E-02	8.87E-03	-6.84042	0.0000
β_2	0.772	1.42E-02	54.4065	0.0000
β_3	1.11E-05	1.37E-06	8.09033	0.0000
β_4	4.67E-06	7.32E-07	6.37355	0.0000
β_5	9.25E-06	1.04E-06	8.91024	0.0000
d	14.629	5.812	2.51679	0.0118
	Function Value			51988.64
	Number of Observations			11158

APPENDIX 6: INDEX FUTURES MISPRICING SERIES

Figure 1

* Introduction of SPDRs: Jan., 29, 1993

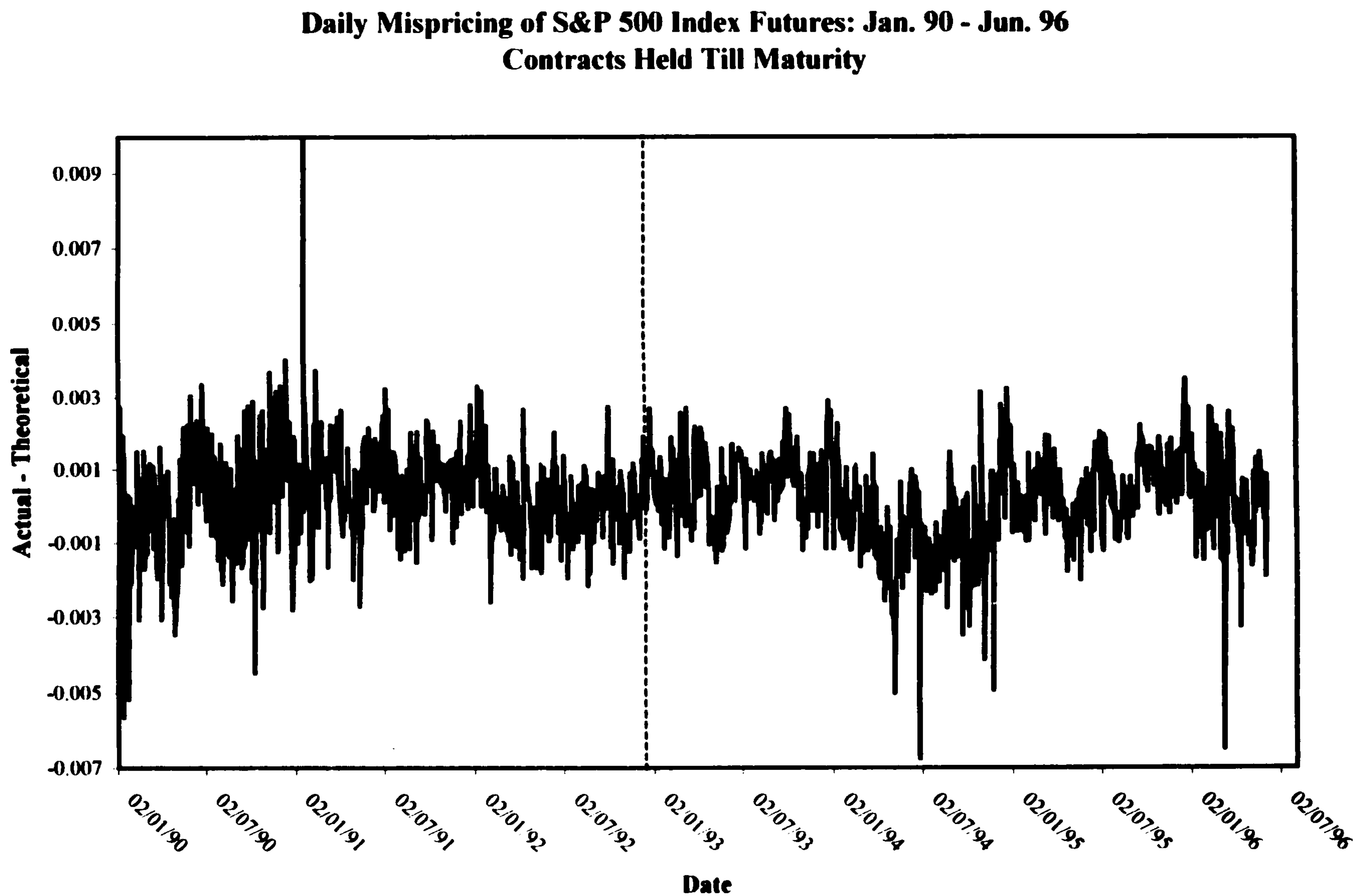

Figure 2

* Inroduction of SPDRs: Jan.. 29, 1993.

Daily Mispricing of S&P 500 Index Futures: Jan. 90 - Jun. 96
Contracts Rolled Over One Week Before Expiration

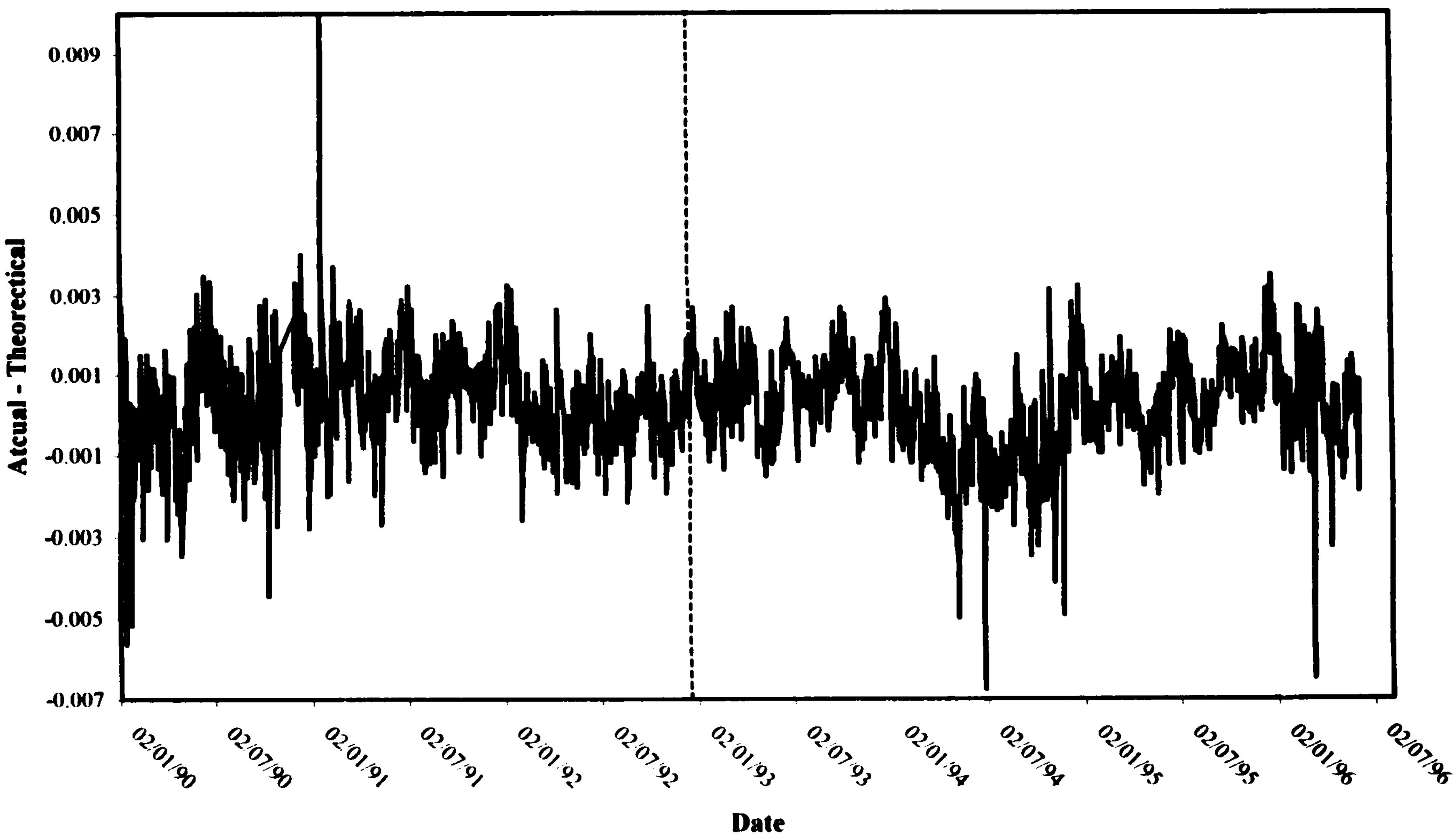

Figure 3

* Introduction of SPDRs: Jan. 29, 1993

Intradaily Mispricing of S&P 500 Index Futures: Jan. 90 - Jun. 96
Contracts Held Till Maturity

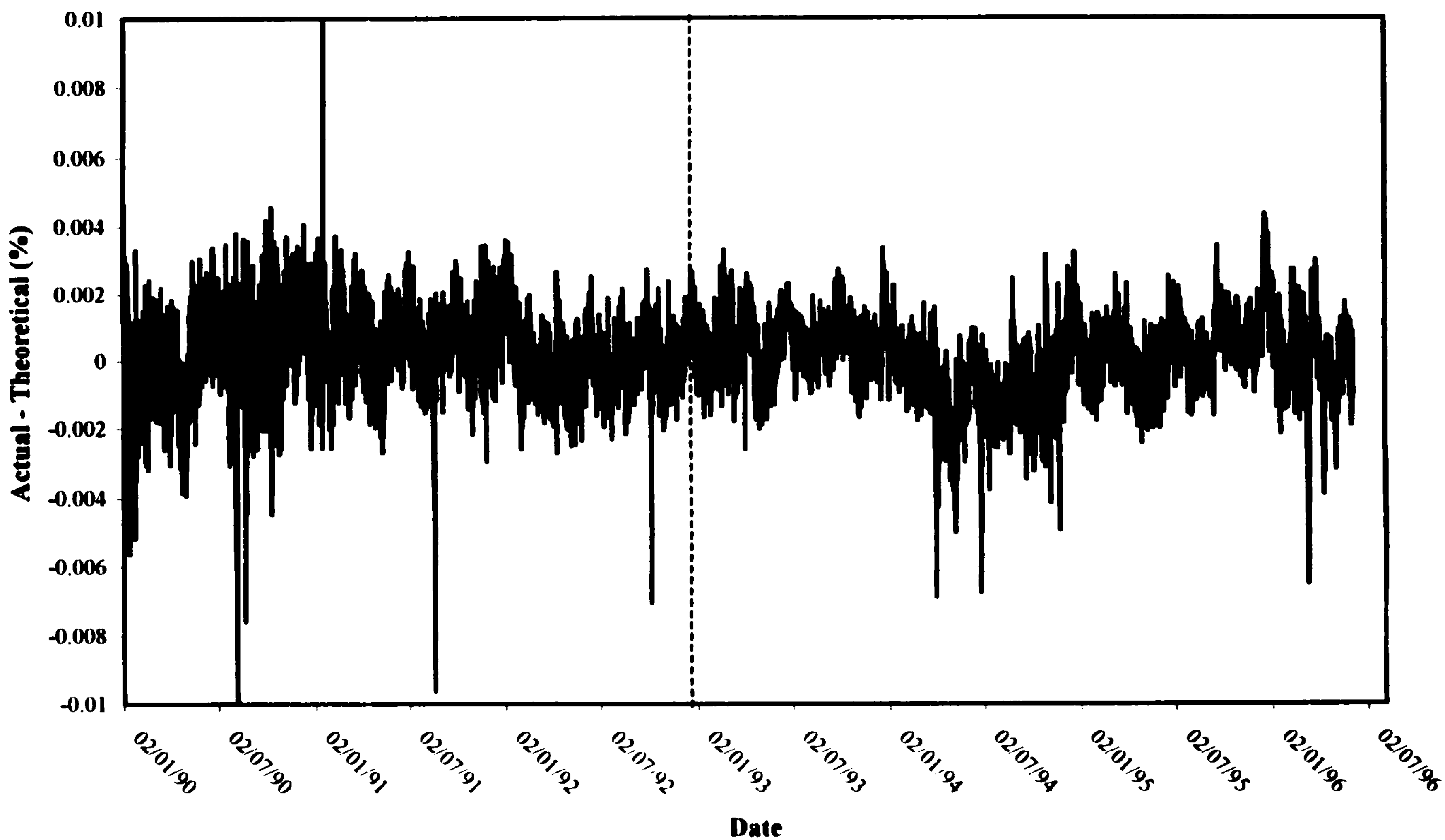

Figure 4

* Introduction of SPDRs: Jan. 29, 1993.