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PRICING OF S&P 100 INDEX OPTIONS BASED ON GARCH VOLATILITY ESTIMATES

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Abstract

This paper is a contribution to the vast literature on the inefficiency in the index options markets. Previous research has found that trading based on implied volatility forecasts do not generate positive profits for the S&P 500 index options but GARCH volatility forecasts do. Trading based on implied volatility forecasts for the S&P 100 index options also fail to generate profits in excess of transaction costs. This paper shows that trading based on GARCH volatility forecast generates profits in excess of transaction costs for the S&P 100 index options hence there is systematic mispricing in the S&P index options markets. GARCH models fair well due to their flexibility to incorporate asymmetric and nonlinear volatility effects. Improved pricing models should work as well or better.

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I. Introduction

Option prices are a function of the current price, the strike price, time to expiration, volatility of the asset price, the risk-free interest rate and the dividends expected during the life of the option. For a non-dividend paying asset, the only nonobservable parameter is the volatility of the asset price. Observed option prices then imply the volatility of the asset as perceived by the market. If an investor differs in his estimate of the volatility of the return of the underlying asset hence the valuation of the option, then, in the absence of transaction costs, he can make positive profits based by trading based on his volatility estimates. This in turn constitutes a test for the efficiency of markets if, given transaction costs, positive profits are possible.

Researchers have reported evidence of mispricing in index call and put options[1] markets. (See Evnine and Rudd (1985), Chance (1986), (1987)), Ackert and Tian (1998), Kamara and Miller (1995)). Mispricing, as a general rule, should be considered as evidence of market inefficiency, since investors who are able to price options correctly should be able to generate positive profits until market efficiency is restored. However, in a market with constraints, inefficiency may persist if investors are not able to take advantage of the profit opportunities. Ackert and Tian (2001) argue that this is the case in the S&P 500 options markets, that there is mispricing in the call and put options which cannot be eliminated by arbitrage. They also argue that mispricing

[1] An option on a financial asset gives the owner either the right to buy (*call option)* or the right to sell (*put option)* the asset at a prespecified price (*strike price)* on or before a prespecified date *(expiration date)*. An option that can only be exercised on the day of expiration is a *European option*, an option that can be exercised any time before it expires is an *American option.*

should not be considered as an indication of the inefficiency of the market if constraints do not enable arbitrageurs from profiting from the mispriced assets[2].

Noh, Engle and Kane (1993) test the efficiency of the S&P 500 index option market based on the performance of two volatility forecast models. They find that the GARCH volatility forecast model generates significantly positive profits after transaction costs with near-the-money straddle trading whereas the implied volatility regression model fails to do so. Harvey and Whaley (1992) test the efficiency of the S&P 100 option index market using implied volatility methods to forecast future volatility and find that excess returns are not possible. Would GARCH volatility forecast models be able to generate positive profits in the S&P 100 index options as well? The aim of this paper is to test the efficiency of the S&P 100 index option market using a GARCH forecasting model and see if near-the-money straddle trading can generate positive profits after transaction costs in S&P 100 index options. The specification Noh, Engle and Kane have adopted for the S&P 500 index serves as a starting point but is modified to allow for changes in volatility around the option expiration dates. We find that GARCH volatility forecast models indeed generate profits in excess of transaction costs for the S&P 100 index options and indicate a systematic mispricing of S&P index options.

The paper is organized as follows. The next section provides a summary of the existing literature on the inefficiency in the index option markets and methods used to forecast volatility. Literature utilizing GARCH specifications are discussed in greater detail. Section 3 introduces the GARCH specifications that we use and discusses the estimated results. Sections 4 and 5 describe the data

[2] A similar analysis on the Hang Seng index options is given by Duan and Zhang (2001).

and the trading experiment based on the GARCH forecasting models. The last section provides a summary of the major findings.

II. Literature Review

There is a vast literature on the inefficiency of index option markets. Noh, Engle and Kane (1993,1994) find evidence for the inefficiency in the S&P 500 index option markets, and Ackert and Tian (1998), Duan and Zhang (2001), Kamara and Miller (1998) report evidence of mispricing in index call and put options. Ackert and Tian (2001) report violations in option pricing relationships for the S&P 500 index options based on methods that are independent of the option pricing models used.

Existing literature on forecasting the volatility of financial assets, for the most part favors two methodologies. Perhaps the more popular of the two, makes use of the autoregressive conditional heteroskedasticity (ARCH) model proposed by Engle (1982) and generalized by Bollerslev (1986) in its various forms. ARCH models allow conditional variance to change over time and have been used extensively to model stock market volatility which is time-varying in nature. French, Schwert and Stambough (1987), Chou (1988), Pagan and Schwert (1989), Engle and Gonzales-Rivera (1989) and Nelson (1991) have used ARCH models to forecast volatility of stock returns. Option pricing models with stochastic volatility have been developed and applied to several index options. Engle, Kane and Noh (1997) are one of the first to use stochastic volatility models for S&P 500 index options. Lin, Strong and Xu (2001) analyze options on the FTSE 100 index, Duan and Zhang (2001) on the Hang Seng index based on stochastic volatility models.

The most popular alternative to ARCH models, is to use option implied volatility as an estimate of conditional variance. Latane and Rendleman (1976) show that volatility implied by option prices is a better predictor of future volatility than alternatives based on historical price data. Schmalensee and Trippi (1978) use implied volatility as an estimate of conditional voaltility and construct a weighted-average volatility estimate for the asset from implied volatilities of individual options. Day and Lewis (1988) study the changes in volatility around expiration dates and find that the behavior of the implied volatilities for options spanning the expiration dates is consistent with an unexpected increase in market volatility around expiration dates. Schwert (1990) analyzes the behavior of volatility around the stock market crash of 1987 using implied volatility. Stein (1989) finds that longer term options overreact to changes in the implied volatility of short term options. Harvey and Whaley (1991) investigate the effect of infrequent trading on the implied volatility estimates and suggest modifications to improve valuation of the options.

Profits from trading based on volatility forecasts have been used to test the efficiency of markets. Engle, Hong, Kane and Noh (1993) compare returns from trading in NYSE index options based on different variance forecasts. They find that ARCH models show the highest profits and lowest standard deviations and thus are superior to alternatives. Noh, Engle and Kane (1993) test the efficiency of the S&P 500 index option market and find that GARCH forecasting method generates positive profits. Harvey and Whaley (1992) forecast the volatility implied in the S&P 100 and although they test and reject that volatility changes are unpredictable, they find that abnormal returns are not possible.

III. GARCH Specifications

Options expire on the third Friday of the expiration month. There is evidence that markets are more active and volatile around these dates. Stoll and Whaley (1987) document that the volume of trading in the stocks listed on the New York Stock Exchange (NYSE) during the last hour of trading on Fridays when futures contracts expire[3] is twice as much as other Fridays. They also show that the S&P 100 index is more volatile during the last hour of trading on the days that options expire. Day and Lewis (1988) find evidence that the market anticipates higher volatility around expiration dates.

Different GARCH specifications are used to forecast volatility of the S&P 100 returns. All models allow for changes in volatility of daily returns on "special days". There are three kinds of "special days"; Mondays, Tuesdays and monthly expiration dates. Noh, Engle and Kane (1993) estimate the annualized standard deviation of the S&P 500 index returns to be 23.35 % for the period 1986 through 1991, compared to 33.64 % on Mondays and 19.74 % on Tuesdays. In Table 1, we provide different measures of volatility around expiration dates. All the figures in the table are based on daily prices. Rather than a significant increase in volatility, we note an increase in daily returns around expiration. The findings of researchers such as Stoll & Whaley (1987) and Day & Lewis (1988) are based on intraday data, and we fail to find striking rises in volatility based on daily data. However, our findings indicate that expiration dates are indeed special and deserve treatment as such.

Table 1

[3] Futures contracts expire quarterly.

Volatility of S&P 100 Index, Jan 1987 - Jan 1993 *
(Standard Deviations are in Parenthesis)

	Daily Returns	*High - Low*	*(High-Low)/Close*
Overall	0.00056	3.8736	0.0125
	(0.0101)	(2.1)	(0.0075)
Expiration day	0.00323	4.2685	0.0142
	(0.012)	(2.383)	(0.0079)
The last two days before	0.0019	4.234	0.0142
expiration	(0.0129)	(2.35)	(0.0083)
Week of expiration	0.0021	4.0725	0.0137
	(0.011)	(2.2845)	(0.008)

*** October 1987 is excluded.**

Noh, Engle and Kane (1993) suggest the following specification for the volatility of the S&P 500 return series, which we adopt as our starting point to forecast the volatility of the S&P 100 return series:

$$r_t = a_0 + \varepsilon_t, \quad \varepsilon_t \sim N(0, h_t) \tag{1}$$

$$h_t = d_t^{\delta}\left\{b_0 + d_{t-1}^{-\delta}\left(b_1\varepsilon_{t-1}^2 + b_2 h_{t-1}\right)\right\} \tag{2}$$

where r_t is the daily return of the asset at time t and d_t denotes the number of days since the last trading day. If date t is a Monday, h_{t-1} is increased and if date t is a Tuesday h_{t-1} is decreased. There is evidence that variance is smaller when the market is closed[4], that is variance in the middle of the week is greater when compared to variance around the weekend, and the above specification is an attempt to capture this phenomenon.

[4] For example see French & Roll (1986).

To account for the possibility of increased variance around expiration dates[5], (2) can be modified to incorporate this effect to allow for higher volatility around expiration dates.

$$h_t = d_t^{\delta}\left\{b_0 + c_1 \log k_t + d_{t-1}^{-\delta}\left(b_1 \varepsilon_{t-1}^2 + b_2 h_{t-1}\right)\right\} \tag{3}$$

where k_t is number of days to the next expiration date. Evidence on intraday data is to the effect that volatility is higher during the week of expiration, and even more so just before the expiration. We use the natural logarithm of k_t rather than including dummy variables. This model does not treat the effect of k_t on Monday and Tuesday symmetrically. We provide a symmetric alternative given by equation (4).

$$h_t = d_t^{\delta}\left\{b_0 + d_{t-1}^{-\delta}\left(c_1 \log k_t + b_1 \varepsilon_{t-1}^2 + b_2 h_{t-1}\right)\right\} \tag{4}$$

Equation (5) is a linear version of the above models. We estimate this model to investigate whether the nonlinearity in the specification preferred by Noh, Engle and Kane (1993) is justified.

$$h_t = b_0 + c_1 \log k_t + c_2 d_t + c_3 d_{t-1} + b_1 \varepsilon_{t-1}^2 + b_2 h_{t-1} \tag{5}$$

A natural way to model the significantly higher daily returns around expiration dates is by an ARCH-M version of the underlying model. The specification we employed is given by equations (6) and (7).

$$r_t = a_0 + a_1 h_t + \varepsilon_t \tag{6}$$

$$h_t = d_t^{\delta}\left\{b_0 + c_1 \log k_t + d_{t-1}^{-\delta}\left(b_1 \varepsilon_{t-1}^2\right)\right\} \tag{7}$$

[5] Day & Lewis (1988) find evidence in support of this claim.

The models are estimated by maximum likelihood. The results are presented in Table 2. Columns 1 and 2 compare the basic Noh, Engle and Kane (1993) model with and without time to expiration The inclusion of this effect improves the results significantly.[6] The negative coefficient implies a rapidly increasing volatility effect close to the expiration dates. Columns 2 and 3 show that treating Mondays and Tuesdays asymmetrically does not affect the results. Column 4 provides the coefficient estimates for the linear model. This model achieves a function value as good as the other models and also captures the volatility effects of "special days". The coefficient on the Tuesday dummy is negative[7] and significant, implying lower volatility on Tuesdays. Volatility on Mondays is higher, although the coefficient estimate is not significant. The ARCH-M model does not perform well. Including the time to expiration in the return series also does not change the results very much. Likelihood ratio tests for equation (8) versus equation (1) for volatilities given by (3), (4) and (5) do not reject the null that equation (8) provides significant improvement over equation (1).

$$r_t = a_0 + a_1 \log k_t + \varepsilon_t \tag{8}$$

The models are also estimated for the S&P 500 index. The results are provided in Table 3. Once again including the time to expiration in the regression significantly improves the results and the

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[6] Likelihood ratio test rejects the hypothesis that the model given by equations (1) & (3) does not provide a significant improvement over the model given by (1) & (2).

[7] Tuesday dummy is the Monday dummy forwarded one period.

linear specification works just as well as the nonlinear models. The coefficients have the same signs as for the S&P 100 index.

Table 2
S & P 100 Index
(Standard errors are in parenthesis)

	(1) & (2)	(1) & (3)	(1) & (4)	(1) & (5)	(6) & (3)
a_0	0.000868	0.00098	0.00098	0.00102	0.0005
	(0.00029)	(0.0003)	(0.0003)	(0.00029)	(0.00053)
a_1					-0.5173
					(3.862)
b_0	0.000012	0.000036	0.0000345	0.000053	0.000129
	(0.000002)	(0.000004)	(0.000004)	(0.000005)	(0.000009)
b_1	0.1263	0.1298	0.1309	0.1398	0.2299
	(0.01296)	(0.0124)	(0.0122)	(0.0076)	(0.0197)
b_2	0.7816	0.7639	0.7625	0.7720	
	(0.02387)	(0.0211)	(0.0204)	(0.0194)	
δ	0.2856	0.2825	0.2602		0.4830
	(0.0594)	(0.0529)	(0.0528)		(0.04834)
c_1		-0.0000095	-0.0000092	-0.0000081	-0.00001
		(0.0000015)	(0.0000016)	(0.0000017)	(0.000003)
c_2				0.00000349	
				(0.000004)	
c_3				-0.000018	
				(0.0000038)	
# observations	1261	1261	1261	1261	1261
Function Value	5067.17	5078.92	5077.17	5078.95	5013.48

Table 3
S & P 500 Index
(Standard errors are in parenthesis)

	(1) &(2)	(1) & (3)	(1) & (4)	(1) & (5)
a_0	0.00091	0.00104	0.00103	0.00106
	(0.00027)	(0.00028)	(0.00029)	(0.00028)
b_0	0.00001	0.00003	0.000028	0.00004
	(0.000001)	(0.000004)	(0.000004)	(0.000004)
b_1	0.13661	0.1421	0.1432	0.1512
	(0.01357)	(0.0137)	(0.0135)	(0.0079)
b_2	0.76206	0.7462	0.7445	0.7583
	(0.02446)	(0.0233)	(0.0227)	(0.0205)
δ	0.30665	0.2975	0.2812	
	(0.05904)	(0.0553)	(0.0550)	
c_1		-0.000007	-0.000007	-0.000005
		(0.000001)	(0.000001)	(0.0000015)
c_2				0.0000027
				(0.000004)
c_3				-0.000016
				(0.0000035)
# observations	1261	1261	1261	1261
Function Value	5149.40	5157.09	5155.55	5156.52

IV. Trading Experiment

The model given by equations (1) & (5) is estimated using the past 600 rolling observations of the S&P 100 index returns to update the parameter estimates. These estimates are used to forecast volatility through the life of the option as follows;

$$h_{t+1}|t = b_0 + c_1 \log k_{t+1} + c_2 d_{t+1} + c_3 d_t + b_1 \varepsilon_t^2 + b_2 h_t$$

$$h_{t+i}|t = b_0 + c_1 \log k_{t+i} + c_2 d_{t+i} + c_3 d_{t+i-1} + b_1 E(\varepsilon_{t+i-1}^2 | t) + b_2 h_{t+i-1}|t$$

$$h_{t+i}|t = b_0 + c_1 \log k_{t+i} + c_2 d_{t+i} + c_3 d_{t+i-1} + (b_1 + b)_2 h_{t+i-1}|t \qquad i = 2,3,\ldots,\tau$$

where $h_{t+i}|t$ and $\varepsilon_{t+i}|t$ denote predictions at time t. Call and put option prices can then be calculated using the Black-Scholes model.

$$C_{t+1,t+1+\tau} = I_t N(d_1) - Ee^{-r_t \tau} N(d_2)$$

$$P_{t+1,t+1+\tau} = I_t (N(d_1) - 1) + Ee^{-r_t \tau}(1 - N(d_2))$$

$$d_1 = \frac{\ln(I_t / E) + (r_t + 1/2\sigma^2_{t+1,t+1+\tau})\tau}{\sigma_{t+1,t+1+\tau}\sqrt{\tau}}$$

$$d_2 = d_1 - \sigma_{t+1,t+1+\tau}\sqrt{\tau}$$

$$\sigma_{t+1,t+1+\tau} = (1/\tau)\sum_{i=2}^{\tau+1} h_{t+i}|t$$

where $C_{t+1,t+1+\tau}, P_{t+1,t+1+\tau}$ denote Black-Scholes call and put option price forecasts respectively, I_t is the closing price, E is the exercise price, r_t is the risk-free interest rate, $\sigma_{t+1,t+1+\tau}$ is the volatility prediction for the life of the option, $N(x)$ is the cumulative probability distribution for a standardized normal variable and τ is the time to expiration.

A more sophisticated option pricing model, in particular one which can explicitly take into account stochastic variance should be applied to produce more realistic should-be option prices. However, the standard Black-Scholes which incorporates forecasts of volatility based on GARCH models suffices to produce evidence of market inefficiency by showing that excess profits are possible. We acknowledge the need to use improved option-pricing models to generate "correct" option prices.[8]

V. Data

S&P 100 and S&P 500 index option data as provided by the Chicago Board of Options Exchange for the period January 1989 through December 1991 are used in the analysis. Data for the underlying are available from January 1987 through December 1991. The Treasury bill rate from Citibase is used for the risk-free interest rate.

If the investor believes that volatility is going to be higher than what is perceived by the market, he can buy a call option and a put option with the same strike price and expiration date. This is called a *straddle*. To make profits using this information he would buy a straddle at the current price (*at-the-money*) since they are the most sensitive instruments to changes in volatility. If indeed volatility is higher then the price of both options

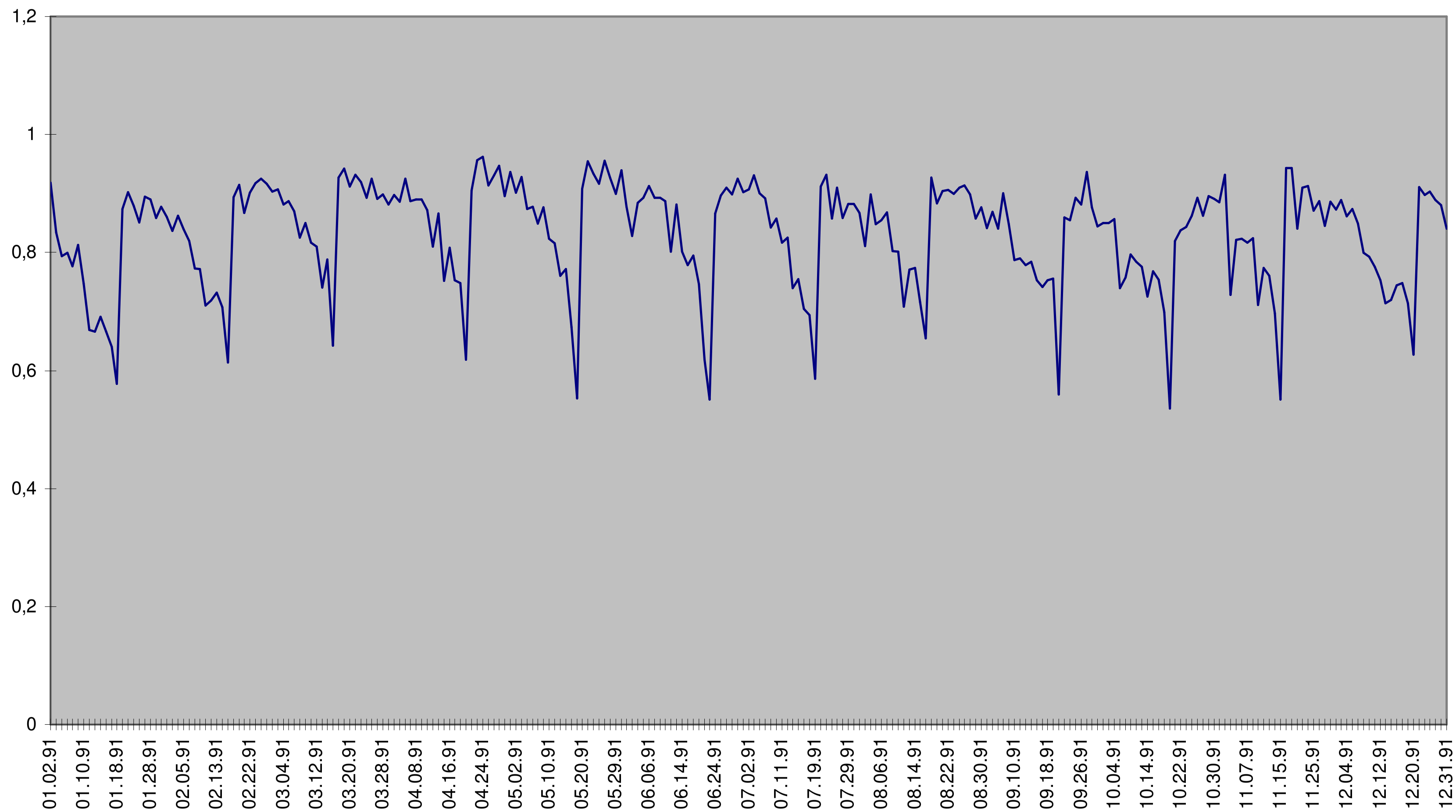
[8] Several methodologies exist. For a review of option pricing with stochastic volatility see Lin, Strong and Xu (2001).

increases because of the change in volatility, and if most of the price change is in one direction then one option becomes significantly more valuable since the strike price is now quite different from the current price.

Trading is done on nearest term at-the-money call and put options. We compare the call and put prices generated by our model and if the price is sufficiently higher (to cover transaction costs), we buy the straddle, otherwise we don't trade. We only hold a position for a day. We buy at the close and sell at the next day's close if we haven't exited the market before that. We exit the market when we make the threshold level of profit on the call or on the put or at the end of the day. We assume there is no slippage. Daily trading volume in the nearest term option is on average about 80 %. During the last week it goes up to 90 %. Given the liquidity in the market, our assumption about slippage is well justified.

Tables 4-9 provide average annualized rates of return from straddle trading near-the-money options for different levels of transaction costs and exit thresholds. Two different sets of trading strategies are employed. Tables 4-6 are based on straddle trading where a call for every put is bought. Tables 7-9 bet the same amount of money on calls and puts. For each strategy, we buy the at-the-money straddle, the nearest in-the-money straddle and the nearest out-the-money straddle. The results indicate that excess profits are possible and the right exit strategy can improve the results dramatically.

Figure 1
Trading Volume in Next to Expire Option



As an example, the at-the-money straddle trading combined with an exit strategy that quits the market when the 30% profit threshold is reached generates average annualized rates of return of 221% when transaction costs are $3 per contract. This is a conservative level of transaction costs for the period of the trading experiment and excess profits are possible. Over the 660 days this experiment was done, 228 trades were made. This amounts to about one trade for every three trading days, which is quite frequent. The average daily return over the 660 days is 0.6 % after transaction costs.

As a final note, straddle trading based on the GARCH forecasting model does better than the simple trading strategy of trading every day and exiting the market at the end of each day. Exit strategies improve the results for this trading strategy as well. These results are not presented here but are available upon request.

VI. Conclusion

This paper is a contribution to the vast literature on the inefficiency in the index options markets. Previous research has found that trading based on implied volatility forecasts do not generate positive profits for the S&P 500 index options but GARCH volatility forecasts do. Trading based on implied volatility forecasts for the S&P 100 index options also fail to generate profits in excess of transaction costs. This paper shows that trading based on GARCH volatility forecast generates profits in excess of transaction costs for the S&P 100 index options hence there is systematic mispricing in the S&P index options markets.

We have estimated various GARCH models for the S&P 100 and S&P 500 index returns. We find that the number of days to expiration is an important factor in predicting future volatility. We have traded straddles based on our forecasting methodology and were able to make positive profits. To the extent that this constitutes a test for efficient markets, we conclude that the S&P 100 index options market is inefficient and there is potential for speculative profits.

There are more sophisticated methods of pricing options with stochastic volatility than the one we use to price options in this paper, hence we do not argue that we correctly price the options when the market does not.

Table 4

Average annualized rates of return from trading with at-the-money options

Equal numbers of calls and puts

Exit Strategy	**Transaction costs ($ per contract)**										
	0	**$1**	**$2**	**$3**	**$4**	**$5**	**$6**	**$7**	**$8**	**$9**	**$10**
0	1617%	1544%	1471%	1398%	1325%	1252%	1179%	1105%	1032%	959%	886%
10%	510%	436%	363%	290%	217%	144%	71%	-2%	-76%	-149%	-222%
20%	106%	33%	-40%	-114%	-187%	-260%	-333%	-406%	-479%	-552%	-626%
30%	440%	367%	294%	221%	148%	75%	1%	-72%	-145%	-218%	-291%
40%	205%	132%	59%	-14%	-87%	-160%	-234%	-307%	-380%	-453%	-526%
50%	106%	32%	-41%	-114%	-187%	-260%	-333%	-406%	-480%	-553%	-626%
60%	58%	-15%	-89%	-162%	-235%	-308%	-381%	-454%	-527%	-601%	-674%
70%	82%	9%	-65%	-138%	-211%	-284%	-357%	-430%	-503%	-577%	-650%
80%	97%	24%	-50%	-123%	-196%	-269%	-342%	-415%	-488%	-561%	-635%
90%	63%	-10%	-83%	-156%	-230%	-303%	-376%	-449%	-522%	-595%	-668%
100%	51%	-23%	-96%	-169%	-242%	-315%	-388%	-461%	-535%	-608%	-681%

Table 5

Average annualized rates of return from trading the nearest in-the-money option

Equal numbers of calls and puts

Exit Strategy	**Transaction costs ($ per contract)**										
	0	**$1**	**$2**	**$3**	**$4**	**$5**	**$6**	**$7**	**$8**	**$9**	**$10**
0	1498%	1418%	1337%	1257%	1176%	1096%	1015%	935%	855%	774%	694%
10%	438%	358%	278%	197%	117%	36%	-44%	-124%	-205%	-285%	-366%
20%	-18%	-98%	-179%	-259%	-340%	-420%	-500%	-581%	-661%	-742%	-822%
30%	219%	139%	58%	-22%	-103%	-183%	-263%	-344%	-424%	-505%	-585%
40%	-85%	-165%	-246%	-326%	-406%	-487%	-567%	-648%	-728%	-808%	-889%
50%	-163%	-243%	-324%	-404%	-484%	-565%	-645%	-726%	-806%	-886%	-967%
60%	-210%	-291%	-371%	-452%	-532%	-612%	-693%	-773%	-854%	-934%	-1014%
70%	-244%	-325%	-405%	-486%	-566%	-646%	-727%	-807%	-888%	-968%	-1049%
80%	-216%	-297%	-377%	-458%	-538%	-618%	-699%	-779%	-860%	-940%	-1020%
90%	-261%	-341%	-422%	-502%	-582%	-663%	-743%	-824%	-904%	-984%	-1065%
100%	-272%	-352%	-432%	-513%	-593%	-674%	-754%	-834%	-915%	-995%	-1076%

Table 6

Average annualized rates of return from trading the nearest out-the-money option

Equal numbers of calls and puts

Exit strategy	**Transaction costs ($ per contract)**										
	0	**$1**	**$2**	**$3**	**$4**	**$5**	**$6**	**$7**	**$8**	**$9**	**$10**
0	1610%	1516%	1423%	1329%	1235%	1141%	1047%	953%	859%	766%	672%
10%	532%	438%	345%	251%	157%	63%	-31%	-125%	-219%	-312%	-406%
20%	257%	163%	69%	-25%	-119%	-212%	-306%	-400%	-494%	-588%	-682%
30%	256%	162%	68%	-26%	-119%	-213%	-307%	-401%	-495%	-589%	-683%
40%	7%	-86%	-180%	-274%	-368%	-462%	-556%	-650%	-744%	-837%	-931%
50%	-107%	-200%	-294%	-388%	-482%	-576%	-670%	-764%	-857%	-951%	-1045%
60%	-171%	-265%	-359%	-453%	-546%	-640%	-734%	-828%	-922%	-1016%	-1110%
70%	-204%	-298%	-392%	-486%	-580%	-673%	-767%	-861%	-955%	-1049%	-1143%
80%	-218%	-312%	-406%	-500%	-594%	-688%	-781%	-875%	-969%	-1063%	-1157%
90%	-240%	-334%	-427%	-521%	-615%	-709%	-803%	-897%	-991%	-1084%	-1178%
100%	-251%	-345%	-438%	-532%	-626%	-720%	-814%	-908%	-1002%	-1095%	-1189%

Table 7

Average annualized rates of return from trading at-the-money options

Equal $ bets on calls and puts

Exit strategy	**Transaction costs ($ per contract)**										
	0	**$1**	**$2**	**$3**	**$4**	**$5**	**$6**	**$7**	**$8**	**$9**	**$10**
0	1517%	1451%	1384%	1317%	1250%	1184%	1117%	1050%	983%	917%	850%
10%	416%	349%	282%	216%	149%	82%	15%	-51%	-118%	-185%	-252%
20%	24%	-43%	-109%	-176%	-243%	-310%	-376%	-443%	-510%	-577%	-643%
30%	156%	90%	23%	-44%	-111%	-177%	-244%	-311%	-378%	-445%	-511%
40%	-52%	-119%	-185%	-252%	-319%	-386%	-452%	-519%	-586%	-653%	-720%
50%	-134%	-200%	-267%	-334%	-401%	-468%	-534%	-601%	-668%	-735%	-801%
60%	-150%	-217%	-284%	-350%	-417%	-484%	-551%	-617%	-684%	-751%	-818%
70%	-173%	-240%	-307%	-374%	-440%	-507%	-574%	-641%	-708%	-774%	-841%
80%	-136%	-203%	-269%	-336%	-403%	-470%	-537%	-603%	-670%	-737%	-804%
90%	-160%	-227%	-294%	-360%	-427%	-494%	-561%	-627%	-694%	-761%	-828%
100%	-174%	-241%	-308%	-375%	-442%	-508%	-575%	-642%	-709%	-775%	-842%

Table 8

Average annualized rates of return from trading in-the-money options

Equal $ bets on calls and puts

Exit strategy	Transaction costs ($ per contract)										
	0	**$1**	**$2**	**$3**	**$4**	**$5**	**$6**	**$7**	**$8**	**$9**	**$10**
0	1386%	1324%	1263%	1202%	1141%	1079%	1018%	957%	895%	834%	773%
10%	502%	441%	380%	319%	257%	196%	135%	74%	12%	-49%	-110%
20%	157%	95%	34%	-27%	-89%	-150%	-211%	-272%	-334%	-395%	-456%
30%	265%	203%	142%	81%	20%	-42%	-103%	-164%	-225%	-287%	-348%
40%	17%	-44%	-105%	-167%	-228%	-289%	-350%	-412%	-473%	-534%	-596%
50%	-15%	-76%	-138%	-199%	-260%	-321%	-383%	-444%	-505%	-566%	-628%
60%	-33%	-94%	-156%	-217%	-278%	-339%	-401%	-462%	-523%	-584%	-646%
70%	-48%	-109%	-170%	-231%	-293%	-354%	-415%	-476%	-538%	-599%	-660%
80%	11%	-50%	-112%	-173%	-234%	-295%	-357%	-418%	-479%	-540%	-602%
90%	-11%	-72%	-133%	-195%	-256%	-317%	-378%	-440%	-501%	-562%	-624%
100%	-26%	-88%	-149%	-210%	-271%	-333%	-394%	-455%	-516%	-578%	-639%

Table 9

Average annualized rates of return from trading out-the-money options

Equal $ bets on calls and puts

Exit strategy	Transaction costs ($ per contract)										
	0	**$1**	**$2**	**$3**	**$4**	**$5**	**$6**	**$7**	**$8**	**$9**	**$10**
0	1410%	1345%	1280%	1215%	1151%	1086%	1021%	956%	891%	826%	761%
10%	388%	323%	258%	193%	128%	63%	-2%	-67%	-132%	-197%	-262%
20%	131%	66%	1%	-64%	-129%	-194%	-259%	-324%	-388%	-453%	-518%
30%	39%	-26%	-91%	-156%	-221%	-286%	-351%	-416%	-481%	-546%	-611%
40%	-221%	-286%	-351%	-416%	-481%	-546%	-610%	-675%	-740%	-805%	-870%
50%	-338%	-403%	-468%	-533%	-598%	-663%	-728%	-793%	-858%	-923%	-988%
60%	-341%	-406%	-471%	-536%	-601%	-666%	-731%	-796%	-861%	-926%	-991%
70%	-413%	-478%	-543%	-608%	-673%	-738%	-803%	-868%	-933%	-998%	-1063%
80%	-438%	-503%	-568%	-633%	-698%	-763%	-827%	-892%	-957%	-1022%	-1087%
90%	-470%	-535%	-600%	-665%	-730%	-795%	-860%	-925%	-989%	-1054%	-1119%
100%	-484%	-549%	-614%	-679%	-744%	-809%	-874%	-939%	-1004%	-1069%	-1134%

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