Dynamic Volatility Trading Strategies in the Currency Option Market Using Stochastic Volatility Forecasts

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Abstract

The conditional volatility of foreign exchange rates can be predicted with GARCH models, and with implied volatility extracted from currency options. This paper investigates whether the difference in these predictions is economically meaningful. In an efficient market, after accounting for transaction costs and risk, no trading strategy should earn abnormal risk-adjusted returns. In the absence of transaction costs, both the delta-neutral and the straddle trading stratgies lead to significant positive economic profits against the option market, regardless of which volatility prediction method is used. The agent using the Implied Stochastic Volatility Regression method (ISVR) earns larger profits than the agent using the GARCH method. However, after accounting for the transaction costs assumed to equal one percent of market prices, observed profits are not significantly different from zero in most trading strategies; the exception is for an agent using the ISVR method with a 5% price filter. Finally, on risk adjusted basis, the dynamic volatility trading strategies offered better risk-return relation: higher Sharpe ratio, lower correlation with several asset classes, and higher abnormal returns. This is attractive for investors who want to improve the risk-return profile of their portfolio through diversification.

1 Introduction

Several studies on stock index options conclude that volatility changes are statistically predictable. However, it is inconclusive as to whether this predictability is economically meaningful. Harvey and Whaley (1992) observe that while the implied volatility delivers precise forecasts for the S&P 100 index options, abnormal returns are not possible in a trading strategy that takes transaction costs into account. This suggests that predictable time–varying volatility is consistent with market efficiency. In addition, Engel, Kane and Noh (1993) calculate the economic value of volatility forecasts from implied volatility and GARCH models on S&P 500 index options. They find that the GARCH model earns greater profit than does the implied volatility regression model even after taking transaction costs into account.

These studies have focused on stock index options, whereas this paper focuses on foreign currency options. An advantage in using currency options is that the simultaneous recording of exchange rates and option prices alleviates the "nonsynchronous trading problem" encountered in the studies of stock index options. In this paper, prices of the U.S. dollar/German mark (dollar/mark) options traded on the Philadelphia Stock Exchange (PHLX) are analyzed. The dollar/mark currency options are chosen for two reasons: they are highly volatile; and they are the most frequently traded.

In an efficient market, after accounting for transaction costs and risk, no trading strategy should earn abnormal returns. If predictions of volatility changes can be used to generate abnormal risk-adjusted profits, the market efficiency hypothesis will be challenged. If no economic profits are generated, the market efficiency hypothesis is supported. The efficiency of the currency option market is tested based on the performance of the GARCH and the Implied Stochastic Volatility Regression (ISVR) volatility prediction methods. Out-of-sample daily volatilities for the dollar/mark rate are predicted with the ISVR and GARCH methods. The GARCH volatility prediction method is based on the GARCH models of Engle (1982) and Bollerslev (1986). The implied volatilities are extracted from the stochastic volatility model of Hull and White (1987). The hypothesis that market volatility changes are unpredictable is first tested and rejected. The resulting regression formula is modified to predict daily out-of-sample volatility.

A combination of implied volatility and GARCH volatility may only improve volatility forecasts marginally. Recent study by Guo (1996) suggests that the implied variance extracted using the Hull and White (1987) stochastic volatility model from PHLX currency options is an efficient, but biased forecast of the future variance of the exchange rate, and that the MA(60) and GARCH variance forecasts do not contain significant incremental information. These results are consistent with the findings of Fleming (1993) and Jorion (1995) that implied volatility is a dominant, but biased estimator in terms of ex ante forecasting power.

There are at least two reasons to use the Hull and White (1987) model. First, the time-varying nature of exchange rate volatility suggests that the estimated implied volatility from the constant volatility Black-Scholes (1973) model is subject to specification error. Descriptive Statistics of the dollar/mark spot rate returns has a negative skewness and excess kurtosis. This means that the dollar/mark return does not follow lognormal distribution as assumed by the Black-Scholes model. Second, implied volatility estimated from the Hull and White (1987) model has good statistical performance in predicting future realised variance (Guo (1996)).

To get an operational option pricing model, Hull and White (1987) assumes that the volatility risk is independently distributed with the aggregate consumption growth, thus the risk premium of volatility is zero. This assumption may not be true in light of the facts that at-the-money implied volatility is usually observed to be higher than realised volatility. Though the risk premium of volatility may not be zero, it will not affect the trading results of this paper which based on implied volatility estimates. Similar as the practice of option traders using Black-Scholes implied volatility matrix as inputs in their pricing models, this paper uses the Hull and White (1987) model to extract information about market expectation of future volatility from traded option prices, then use the implied volatility forecasts to improve trading performance. In doing so, we take market expectation of future volatility as reflecting an aggregate view of the market participates towards the future movements of exchange rate; the risk premium of volatility and the transaction costs are already embedded in the implied volatility estimates. This approach is different from Melino and Turnbull (1990), where they first estimate the parameters of the stochastic volatility process from historical exchange rate data, then adjust for risk premium parameters in option pricing.

With the prediction of daily volatilities, theoretical option prices are computed and compared with the observed market prices. Corresponding positions are taken to cash in the profit. Two types of dynamic trading strategies are considered: delta–neutral trading and straddles trading. The investment amounts are all standardized to \$100, and agents do not reinvest the profit the next day. Filters are also introduced to improve the profitability of each strategy. Each strategy is evaluated under two situations: with no transaction cost, and with transaction cost.

In the absence of transaction cost, agents using either the GARCH or the ISVR volatility prediction method earn significant positive economic profits against the option market, for both trading strategies. An agent using the ISVR method earns larger profits than an agent using the GARCH method in all three filters. This suggests that traders who can execute the delta-neutral and the straddle trading strategies at the observed market transaction prices can lock in significant profits during the period examined in this paper. However, for a nonmember of an exchange, especially an individual investor who faces higher transaction costs, the magnitude of the correctly predicted volatility changes is generally not large enough to allow for abnormal risk–adjusted profits. After accounting for transaction costs, the economic profits are not significantly different from zero for most trading strategies. The exception is for an agent using the ISVR method with a 5% price filter.

The low correlation of the volatility trading strategies with investment in stocks and bonds markets, combined with its stand alone results (the high Sharpe Ratio), builds a strong and clear argument for diversification in view of Modern Portfolio Theory. A diversified portfolio containing stocks, bonds, and volatility trading strategies could offer better risk/reward profile than a less diversified portfolio.

Section 2 describes data source, an option pricing model, and the procedure to estimate the implied volatility. Section 3 introduces the two volatility prediction models. Section 4 compares the actual and predicted option prices. Section 5 develops dynamic trading strategies to capture the abnormal risk-adjusted profits. Section 6 concludes.

2 Implied Volatility Estimation

2.1 Data Description

Trading records for foreign currency options are taken from the “Foreign Currency Options Pricing History” database of the Philadelphia Stock Exchange (PHLX). The record for each option trading contains: the date of trade, currency and option identification, maturity symbol, strike price, time of trade, and the option premium per contract. The trade-by-trade option prices cover the period from January 1983 to March 1993. Most of the options are American with maturity of less than one year.

Trading prices for American style options on the dollar/mark exchange rates are considered. The dollar/mark currency options are chosen for two reasons: they are highly volatile, and they are the most frequently traded. To provide a manageable dataset, only trading prices for American call and put options on dollar/mark currencies are considered, from January 2, 1991 to March 25, 1993.

The interest rates used are the daily closing quotes of Euro Deposits in terms of the U.S. dollar, and the German mark. The maturities are of 30, 60, and 90 days. The proxies used for intermediate rates are the rates whose maturities are the closest to the option expiration date.

2.2 Hull and White (1987) Stochastic Volatility Model

The stochastic nature of exchange rate volatility suggests that the estimated implied volatility from the constant volatility Black-Scholes (1973) model is subject to specification error. In the literature various stochastic volatility models were developed by Scott (1987), Hull and White (1987,1988), Wiggins (1987), Melino and Turnbull (1990), and Heston (1993). These models make it theoretically attractive to recover the market expectation of future variance from a logically consistent stochastic volatility model.

To meet this challenge, this paper follows Guo (1996) by adopting the model of Hull and White (1987) in the extraction of the implied variance, and seeks to explore the economic implication of the estimated stochastic implied variance. It is assumed that:

(a) The market is frictionless: trading takes place continuously in time, there are no transaction costs, taxes, or short sale restrictions.

(b) The instantaneous risk-free interest rate r_F and domestic/foreign interest differential $b = r_D - r_F$ are known and nonstochastic.

(c) The state variables are the underlying asset $S(t)$ and the instantaneous variance $V(t)$, and the Hull and White (1987) model is based on the following stochastic processes:

$$dS(t) = \phi S(t)dt + \sigma S(t)dw \tag{1}$$

$$dV(t) = \mu V(t)dt + \xi V(t)dz \tag{2}$$

the variable ϕ is a parameter that may depend on $S(t)$, $\sigma(t)$, and t. The variables μ and ξ are assumed to be constant. dz and dw are Wiener processes with instantaneous correlation ρ. Notice that the instantaneous variance $V(t) = \sigma^2(t)$ follows a geometric Brownian Motion, so ξ is the volatility of variance parameter.

If the instantaneous variance is uncorrelated with aggregate consumption (i.e., the random variance has no systematic risk) and the instantaneous correlation ρ between the underlying asset and its variance process is zero, the Hull and White option price C^{HW} (their equation (8)) is the integral of the Black-Scholes price $C^{BS}(\bar{V})$ over the distribution of the mean variance $\bar{V}$,

$$C^{HW}(S_t, \sigma_t^2) = \int C^{BS}(\bar{V})h(\bar{V}|\sigma_t^2)d\bar{V} \tag{3}$$

where h is the conditional distribution of $\bar{V}$, and $\bar{V}$ is the mean variance over the time interval $[t, T]$,

$$\bar{V} = \frac{1}{T}\int_t^T \sigma^2(t)dt.$$

Hull and White (1987) suggested that if the instantaneous variance is uncorrelated with aggregate consumption and the instantaneous correlation between the underlying asset and its variance process is zero, the Hull and White option price $C^{HW}(S_t, \sigma_t^2)$ is the integral of the Black-Scholes price $C^{BS}(\bar{V})$ over the distribution of the mean variance. Furthermore, Hull and White (1987) proposes a power series approximation technique based on expanding Black-Scholes price $C^{BS}(\bar{V})$ in a Taylor series about its expected average variance $E(\bar{V})$,

$$C^{HW}(S_t, \sigma_t^2) \approx C^{BS}(E(\bar{V})) + \frac{1}{2}\frac{\partial^2 C^{BS}(E(\bar{V}))}{\partial \bar{V}^2}E(\bar{V}^2) + \frac{1}{6}\frac{\partial^3 C^{BS}(E(\bar{V}))}{\partial \bar{V}^3}E(\bar{V}^3) \qquad (4)$$

where $E(\bar{V}^2)$ and $E(\bar{V}^3)$ are the second and third central moments of $\bar{V}$. The second and third terms in the equation are essential to capture the so called "smile" effect for PHLX foreign currency options (Bodurtha and Courtadon (1987)). For each day t, the daily implied variance, $\bar{V}_t$, is estimated by nonlinear least squares. It is then considered to be the unbiased estimator of the market expectation of future variance $E(\bar{V})= \bar{V}_t$ in the Hull and White framework (Fleming (1993) and Guo (1996)).

Because the main objective is to design trading strategy that based on the predictive power of implied variance over future variance, it is necessary to estimate the implied variance from options with maturities that can match option maturity. In addition, increasing the number of option prices used to extract the implied variance is also useful in further reducing the measurement error. Therefore, option contracts with maturities ranging from 30 to 90 calendar days (or 20 to 60 trading days) are pooled in the daily implied variance estimation. The number of trades in a day varies significantly across the sample. The average number of trades is around 100 for the dollar/mark options.

The quality of the approximation given by equation (4) depends on the values of the parameters μ and ξ. Hull and White (1987) suggest that for $\mu = 0$ and sufficiently small values of $\xi^2(T-t)$ (ξ with approximate range of 1 to 4), this approximation is very accurate.[1] Values of ξ are estimated from the GARCH(1,1) parameters estimates reported in Table 1. Nelson (1991) shows that as the time interval goes to zero, the GARCH parameter α_1 approaches $\xi\sqrt{dt/2}$. Using daily exchange rates data from January 1991 to March 1993, this suggests an estimate of ξ of 2.126 for the dollar/mark rate.

Because the currency options used in this paper are American-style options, it is impor-

[1] Hull and White (1987) argued that the choice of $\mu = 0$ is empirically justified on the grounds that, for any nonzero μ, options of different maturities would exhibit markedly different implied volatilities, but this was never observed empirically.

tant to adjust for the early exercise premium. This is done by using the Barone-Adesi and Whaley (1987) quadratic approximation method.

2.3 Implied Volatility Estimation Procedure

Suppose that the option market is informationally efficient and that option traders incorporate their expectation of future volatility into the actual trading, then the market expectation of future volatility should be contained in the market prices. The *benchmark* implied volatilities are usually estimated by matching the model prices to the *at-the-money* options prices, and then inverting the Black-Scholes model. As discussed earlier, an advantage of using the stochastic volatility model is to capture the "smile" effect. The approximation (4) of the Hull and White (1987) model allows extraction of the implied volatility from currency options with a wider range of moneyness. The single day averaged implied volatility is estimated by pooling together options with strike price/spot price ratio (moneyness) between 0.8 to 1.2.

The method to extract implied volatility follows the approach of Whaley (1982) and Lamoureux and Lastrapes (1993). For each day t in the sample, the daily average variance, $\hat{\bar{V}}_t = E(\bar{V}|\Omega_t)$, is estimated by nonlinear least squares. That is, $\hat{\bar{V}}_t$ is chosen to minimize the distance between observed option prices on day t and the predicted option prices from the Hull and White (1987) model

$$\min_{\hat{\bar{V}}_t} SSE(\hat{\bar{V}}_t) = \sum_i [CP_{t,i} - CP_{t,i}^{HW}]^2 \tag{5}$$

where i is an index over observations in a given day; $CP_{t,i}$ is the observed market price; $CP_{t,i}^{HW}$ is the theoretical option price given the interest rate differential $r_D - r_F$, strike price/spot price ratio $(X/S)_{t,i}$, and the remaining life of an option $\tau_{t,i}$. The number of trading quotes in a day varies significantly across the sample, but the average number of quotes per day is about 100 for the dollar/mark options.

3 Volatility Prediction Methods

This section introduces two volatility prediction methods: the GARCH and the Implied Stochastic Volatility Regression methods. The difference between these two methods is that while the GARCH volatilities are estimated from the realized returns of the foreign exchange rates, the implied volatilities are estimated from the realized prices of the foreign exchange options.

3.1 GARCH(1,1) Variance Prediction

The GARCH(1,1) model is selected to calculate the GARCH variance forecasts from a class of GARCH models. The GARCH(1,1) model of Bollerslev (1986) is specified as

$$
\begin{aligned}
R_t &= \lambda_0 + \epsilon_t, \qquad \epsilon_t | \epsilon_{t-1}, \epsilon_{t-2}, \ldots \sim N(0, h_t^2) && (6)\\
h_t^2 &= \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1}^2 && (7)\\
h_{t+k,t}^2 &= \alpha_0 + \alpha_1 E[\epsilon_{t+k-1}^2 | \omega_t] + \beta_1 h_{t+k-1,t}^2 && (8)\\
&= \alpha_0 + (\alpha_1 + \beta_1) h_{t+k-1,t}^2, \qquad k = 1, \cdots, N
\end{aligned}
$$

where $R_t = \sqrt{252}\ln(S_t/S_{t-1})$ is the change in the logarithm of the exchange rate ratios from time $t-1$ to t, ϵ_t is assumed to be conditionally normal with mean zero and conditional variance h_t^2, ω_t is the information set. The exchange rate is measured as U.S. dollars per Deutsche mark. The parameter estimates in the variance equation are constrained to be positive, $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta_1 > 0$, and $\alpha_1 + \beta_1 < 1$. The GARCH models are estimated by Maximum Likelihood; the t-statistics are computed using the robust inference procedure proposed by Bollerslev and Wooldridge (1992).

Table 1 and 2 reports the descriptive statistics and parameters estimates. The results are consistent with the literature that the conditional heteroscedasticity in daily spot rates can be represented by a GARCH(1,1) specification (Hsieh (1988, 1989), Baillie and Bollerslev (1989)). Exchange rate changes appear to have zero unconditional means, and almost zero serial correlations. The excess kurtosis is consistent with the documented fat-tail features of the exchange rates. From January 1989 to March 1993, the the GARCH(1,1) estimates of α_1 and β_1 are 0.095 and 0.819, respectively, with t-statistics of 2.87 and 12.84.

To ensure that the forecast horizon of the GARCH(1,1) variance is identical to that of the option maturity, the T-day GARCH variance is constructed by recursive substitution of the one period ahead GARCH(1,1) variance forecast $h^2_{t+1,t}$ to obtain a k-period ahead prediction of the conditional variance $h^2_{t+k,t}$, then the predictions are averaged over the forecast period. For out of sample prediction, parameters estimated from the previous year are used in the GARCH specification to predict future average variance at each time t.

By mathematical induction, we have:

$$h^2_{t+k,t} = \alpha_0[\frac{1-(\alpha_1+\beta_1)^{k-1}}{1-(\alpha_1+\beta_1)}] + (\alpha_1+\beta_1)^{k-1} h^2_{t+1,t} \tag{9}$$

Therefore, the T period ahead average GARCH variance forecast is calculated as

$$\sigma^2_{G,t} = \frac{1}{T}(\sum_{k=1}^{T} h^2_{t+k,t}) \tag{10}$$

3.2 Implied Stochastic Volatility Regression Method

This section first tests the hypothesis that the changes of implied volatility are unpredictable. After rejecting this hypothesis, the dynamic properties of the implied volatility is investigated and the resulting regression formula is modified to predict one period ahead out-of-sample volatility.

Summary statistics of the implied volatilities for call and put options are reported in Table 3. The average implied volatility is 0.126 for calls, and 0.125 for puts. The positive and significant serial correlation of the implied volatility indicates substantial persistence in the level of volatility. The autocorrelation declines gradually at long lags. However, the modified Dickey–Fuller tests reject the unit root hypothesis of the implied volatilities at the 5% significant level. The first order correlation of the first difference of the daily implied volatility estimates is -0.247 for puts, -0.161 for calls. The autocorrelation and the Dickey–Fuller tests demonstrate that the estimated implied volatilities are stationary and mean-reverting.

The changes of the implied call and put volatilities are regressed over several variables in the information set, including lagged implied call and put volatilities, lagged changes of interest rate differentials, and lagged exchange rates. The regression is specified as follows:

$$\Delta V_t = \alpha_0+\alpha_1 D_{t,1}+\alpha_2 D_{t,5}+\sum_{i=1}^{3}\beta_i \Delta V_{P,t-i}+\sum_{j=1}^{3}\gamma_j \Delta V_{C,t-j}+\sum_{k=0}^{2}\delta_k R_{t-k}+\delta_{ABS}|R_t|+\theta_1 DF_{t-1}+\epsilon_t \tag{11}$$

where ΔV_t represents either $\Delta V_{C,t}$ or $\Delta V_{P,t}$; $R_t = \sqrt{252}\cdot\log(S_t/S_{t-1})$ is the annualized change in the logarithm of the exchange rate; $DF_t = RD_t - RF_t$ is the domestic–foreign interest rate differential based on the daily quotes of 90-day T-bills; $D_{t,1}$ and $D_{t,5}$ are dummy variables for Monday and Friday.

Table 4 reports the results of these regressions for the sample period from 1991 to 1993. All t–statistics are based on the heteroscedasticity consistent standard errors of White (1980). The Monday dummy has no significant effect in either the call or put regressions; while the Friday dummy only has a significant positive coefficient for the put volatility.

The largest explanatory power in both regressions comes from the corresponding lagged values of implied call or put volatilities. These regressions also confirm that the implied volatilities are mean-reverting processes. Notice the significant negative estimates of coefficients (γ_1,γ_2,γ_3) in the call regression ($\Delta V_{C,t}$), and (β_1,β_2,β_3) in the put regression ($\Delta V_{P,t}$).

The inclusion of the contemporaneous and the lagged values of the log of exchange rate changes enables us to study the intertemporal relationship between the exchange rates and the volatility changes. In addition, to capture the possible asymmetry of the contemporaneous relationship, the absolute value of the contemporaneous exchange rate change $|R_t|$ is added to the regression. The estimated coefficients of the contemporaneous, the lagged one and lagged two period exchange rates $(\delta_0, \delta_1, \delta_2)$, are all statistically insignificant. The estimated coefficient for $|R_t|$ is also statistically insignificant, which suggests that there is no asymmetric relationship between the size of exchange rates changes and the contemporaneous changes in its volatility.

The estimates of θ_0 and θ_1 suggest that the contemporaneous and lagged values of interest rates differentials have no significant explanatory power in predicting out-of-sample volatility changes.

Generally speaking, these regressions show that the changes in both the implied call and put volatilities are predictable. The $\bar{R}^2$ is 0.185 for the call regression and 0.255 for the put regression. The implied volatility exhibits no strong relationship with the contemporaneous exchange rate. There is no evidence of asymmetric relationship between the size of exchange rates changes and the contemporaneous volatility. Also the contemporaneous and intertemporal interest rate differentials have no significant explanatory power in predicting the changes of the implied call or put volatilities.

Based on the above evidence, the regression equation is modified to predict the one-period ahead volatility,

$$\Delta V_{C,t} = \hat{\alpha}_0 + \hat{\alpha}_1 D_{t,1} + \hat{\alpha}_2 D_{t,5} + \sum_{i=1}^{3} \hat{\beta}_i \Delta V_{P,t-i} + \sum_{j=1}^{3} \hat{\gamma}_j \Delta V_{C,t-j} \tag{12}$$

$$\Delta V_{P,t} = \hat{\alpha}_0 + \hat{\alpha}_1 D_{t,1} + \hat{\alpha}_2 D_{t,5} + \sum_{i=1}^{3} \hat{\beta}_i \Delta V_{P,t-i} + \sum_{j=1}^{3} \hat{\gamma}_j \Delta V_{C,t-j} \tag{13}$$

where $\Delta V_{C,t}$ and $\Delta V_{P,t}$ are changes of call and put option implied volatilities, respectively. To ensure out of sample prediction, parameters estimated from the previous year are used in the ISVR specification to predict future variance at each time t.

4 Pricing Options Using Predicted Volatility

In order to price the foreign currency options, it is necessary to obtain the predictions of daily volatilities. As discussed in section 3, two approaches to predict volatilities are the ISVR and the GARCH methods. For the predictive tests of this paper, the daily volatility is predicted by both the GARCH and the ISVR methods. Along with the predicted volatilities, the current exchange rates and the interest rates, the option prices are computed using the Hull and White (1987) model.

Descriptive statistics for the actual and the predicted option prices are reported in Table 5. The first part of the table shows that for both the GARCH and the ISVR methods, the predicted prices of calls and puts are on average higher than the observed market prices. To examine in detail the differences between the observed market prices and the model prices, the following regressions are estimated separately for calls and puts

$$C_t = \alpha_0 + \alpha_1 \hat{C}_t + \epsilon_t \tag{14}$$

where C_t is the market price, $\hat{C}_t$ is the model price, and ϵ_t is the error term.

The model provides an unbiased estimate of the actual prices if $\alpha_0 = 0$ and $\alpha_1 = 1$. This hypothesis is tested using the Wald statistic that is asymptotically distributed as $\chi^2(2)$. The large number of observations (227,589 calls, 409,892 puts) implies that even small mispricings are evident in the regressions. Table 4 shows that for all cases of call and put options, the null hypothesis of unbiasedness can be overwhelmingly rejected.

In prices predicted by the ISVR method, the $\hat{\alpha}_1$ coefficient is always less than one and $\hat{\alpha}_0$ is always positive. This suggests that the model prices based on the ISVR method tend to underpredict low priced (less than $\frac{\hat{\alpha}_0}{1-\hat{\alpha}_1}$) calls and puts, and overpredict high-priced calls and puts.

The model prices predicted by the GARCH method suggest a slightly different story. For calls, the estimated $\hat{\alpha}_1$ is less than one and the estimated $\hat{\alpha}_0$ is negative. This indicates that the predicted prices from the GARCH method tend to overpredict calls. For puts, the $\hat{\alpha}_1$ is larger than one and $\hat{\alpha}_0$ is negative. This suggests that the predicted prices obtained from the GARCH method overvalue puts that are less than $\frac{\hat{\alpha}_0}{1-\hat{\alpha}_1}$, and undervalue puts that are higher than $\frac{\hat{\alpha}_0}{1-\hat{\alpha}_1}$).

5 Economic Profits for Predictable Volatility Changes

Sections 3 and 4 indicate that the conditional volatility of the dollar/mark exchange rate is statistically predictable using either the ISVR or the GARCH model. This section is devoted to the investigation of whether this predictability is significant enough to generate abnormal profit opportunities. In an efficient market, after accounting for transaction costs and risk, no trading strategy should earn abnormal returns. The market efficiency hypothesis is tested based on the so-called *ex post* trading strategy, which assumes that the agent can trade at the market prices that indicate deviations from the model prices (see Galai (1977), Shastri and Tandon (1986)). Furthermore, the trading strategies require the option positions to be hedged against the exchange rate movements. Two hedging methods are developed: delta-neutral hedging and straddle hedging. In calculating the hedged returns, I assume that the model of Hull and White (1987) is valid.

5.1 Delta-Neutral Trading Strategy

The delta-neutral portfolio consists of selling or buying options and taking positions on holding or selling foreign currencies. Generally speaking, if the hedging position can be adjusted frequently, the *delta-neutral* trading strategy works well for the Black-Scholes (1973) model.[2]

The *delta-hedging* trading strategy proceeds as follows. On day t, each agent applies a volatility prediction method (ISVR or GARCH) to forecast volatility and compute the theoretical option price. The agent is allowed to change the position daily by buying the option if it is undervalued, or selling it if it is overvalued. The restriction imposed is that \$100 worth of options and foreign currency are always bought and sold, and that the agent does not reinvest the profit the next day. Next, the agent compares the theoretical price C_t^M with the actual trading price C_t^A. If $C_t^M > C_t^A$, so the option appears underpriced, the agent decides to buy the option, and delta-hedges the position by buying or selling foreign currency. The hedged position is liquidated at day $t+1$, and the agent obtains the return. If $C_t^M < C_t^A$, so the option appears overpriced, the agent sells options, delta-hedges the position by buying or selling foreign currency, and invests the \$100 plus the proceeds from selling the options on a risk-free asset. On day $t+1$, the hedged position is liquidated, and the agent obtains the return. The return formula for various strategies are as follows:
(1) if the agent buys call option at price C_t^A and sells foreign currency at price S_t, the

[2] Hull and White (1987b) compares the relative performance of various hedging schemes. They find that the Delta-gamma hedging performs well when the traded option has a constant implied volatility and a short time to maturity, but it can perform far worse than Delta-hedging in other situations. They also find that Delta-vega hedging outperforms other hedging schemes when the traded option has a non-constant implied volatility and a long time to maturity.

absolute return is

$$AR_{H,t+1} = n_c \cdot [(C^A_{t+1} - C^A_t) - \delta_c(S_{t+1} - S_t)] + 200 \cdot r_D \tag{15}$$

where δ_c is the *delta* of a American call on one unit of foreign currency, and $n_c = |100/(C^A_t - \delta_c S_t)|$,

(2) if the agent sells call option and buys foreign currency, the absolute return is

$$AR_{H,t+1} = n_c[-(C^A_{t+1} - C^A_t) + \delta_c(S_{t+1} - S_t)] \tag{16}$$

where $n_c = 100/(-C^A_t + \delta_c S_t)$,

(3) if the agent buys put option and buys foreign currency, the absolute return is

$$AR_{H,t+1} = n_p[(P^A_{t+1} - P^A_t) - \delta_p(S_{t+1} - S_t)] \tag{17}$$

where δ_p is the *delta* of a American put on one unit of foreign currency, $n_p = 100/(P^A_t - \delta_p S_t)$,

(4) if the agent sells put option and sells foreign currency, the absolute return is

$$AR_{H,t+1} = n_p[-(P^A_{t+1} - P^A_t) + \delta_p(S_{t+1} - S_t)] + 200 \cdot r_D \tag{18}$$

where $n_p = |100/(-P^A_t + \delta_p S_t)|$.

With the initial investments of \$100, the relative return for \$1 of investment is

$$RR_{H,t+1} = AR_{H,t+1}/100 \tag{19}$$

Table 6 reports the summary statistics of annualized return of the delta-neutral trading strategy for the full sample period. Before accounting for transaction costs, the agent using the ISVR method makes more profit than the agent using the GARCH method. For the ISVR method, the annualized returns are 13.92% for calls and 14.93% for puts, with Sharpe ratio of 2.6 and 3.28, respectively. For the GARCH method, the annualized returns are 10.12% for calls and 5.06% for puts, with Sharpe ratio of 0.94 and -0.48, respectively.

To evaluate the performance of the trading strategies on a risk adjusted basis, the following asset classes are selected: the S&P 500 index, MSCI world equity index for equity markets, J.P. Morgan global bond index, J.P. Morgan U.S. government bond index, J.P. Morgan Germany government bond index, Goldman Sachs commodity index. For the same sample period, the annualized return for the 1 year U.S. Treasury Bill Rate is 4.67 %, the annualized return for the S&P 500 Stock Index is 13.7%, with a Sharpe ratio of 0.75.

To test whether the price deviations are large enough to cover the transaction costs, filters with values of 2% and 5% of market prices are applied. Under these filters, options are only traded when the predicted price deviation is larger than the filter value. When the value of the filter increases, the number of trades decreases, and the agent is allowed to invest in the risk-free asset on no trading days. The results of using different filters are also reported in Table 6. Increasing the value of the filter increases the profitability. For the whole sample period, the daily average returns for agents using the ISVR and the GARCH methods are significantly greater than zero, but the returns for agents using the ISVR method are larger than returns for agents using the GARCH method in all three filters. In particular, with a 5% filter and no transaction costs, the agent using the ISVR method earns an annualized return of 27.58% for calls, and 22.56% for puts, while the agent using the GARCH method earns merely 15.67% for calls and 8.09% for puts.

To demonstrate that the delta-neutral trading strategy may lead to abnormal profits, the effect of transaction costs must be included. Studies by Black-Scholes (1972), Galai (1976), Shastri and Tandon (1986), and Harvey and Whaley (1991) on option trading strategies find that after accounting for transaction costs, the documented positive excess profits are generally not significantly different from zero. I assume that the transaction costs consist of a round-trip cost of one tick plus commissions. The per contract transaction charge for currency options at the PHLX is $0.28 for Customer Execution, $0.23 for Firms, $0.07 for Registered Option Trader and Specialist, and $0.05 for Floor Brokerage Transaction. Each dollar/mark option contract contains 62,500 marks. The minimum tick size on the PHLX is $.0001 for currency options, or $6.25 per contract. It is likely that an option identified as overpriced (underpriced) will have traded at the ask (bid), so actual selling (buying) this option in an arbitrage trade would most likely occur at a price one tick lower (higher). For most of the options selected (near-the-money, less than six months maturity), the option premium for each contract is between \$400 to \$800. We can estimate that the transaction costs range from 0.78%-1.56% of contract value plus commissions. For illustration purpose, the cost of changing investment position is assumed to be 1% of option prices.[3] For example, the net return for buying calls and selling foreign currency with transaction costs becomes

$$NAR_{H,t+1} = n_c \cdot [(C^A_{t+1} - C^A_t) - \delta_c(S_{t+1} - S_t) - 0.01 \cdot (C^A_{t+1} + C^A_t)] + 200 \cdot r_D \qquad (20)$$

It is evident that abnormal profits are dramatically reduced after accounting for transaction costs. For a one day holding period, transaction costs equal to 1% of the option price eliminate the hedged return for the GARCH method, while the ISVR method can only lock in a significant profit with a 5% filter.

5.2 Straddles Trading Strategy

A straddle is a pair of call and put options with the same maturity and striking price. An advantage of straddle trading is that it provides a natural hedge to the straddle holder since the call and put positions offset each other. Straddle data are collected from the daily trading record of dollar/mark options. Only options with at least fifteen days to expiration are considered. To avoid using deep-in or out-of-money options, options with moneyness (S/X) within the range of [0.85, 1.15]) are selected.

The straddle trading strategy proceeds as follows. Assume that investments of \$100 worth of straddles are always bought and sold, and agents do not reinvest the profit the next day. On day t, the agent applies either the ISVR or the GARCH method to forecast future volatility, and calculates the straddle price. The model price $C^M_t + P^M_t$ is compared with the actual closing price $C^A_t + P^A_t$. If $C^M_t + P^M_t > C^A_t + P^A_t$, so the straddle appears underpriced,

[3]This assumption is more justified to institutional investors for the following reasons: (1) the bid/ask spread can be expressed in this way; (2) commission is approximately proportional to trading volume; (3) the effect of putting in an order on the market is positively related to the size of the order. Although absolute cost can be viewed as fixed cost (e.g., computer, salary), it can normally be deducted on an annual basis; and its number is relatively independent of trading volume.

the agent buys \$100 worth of straddles. If $C_t^M + P_t^M < C_t^A + P_t^A$, so the straddle appears overpriced, the agent sells the straddle, and invests in a risk-free asset with the initial \$100 plus the proceeds (assumed to be \$100) obtained from selling the straddles. On day $t+1$, the agent liquidates the position and claims the return.

If the agent buys the straddles, the absolute return is

$$AR_{B,t+1} = n_s \cdot [(C_{t+1}^A - C_t^A) + (P_{t+1}^A - P_t^A)] \tag{21}$$

where $n_s = 100/(C_t^A + P_t^A)$.

If the agent sells the straddles, the absolute return is

$$AR_{S,t+1} = -n_s \cdot [(C_{t+1}^A - C_t^A) + (P_{t+1}^A - P_t^A)] + 200 \cdot r_D \tag{22}$$

where $n_s = 100/(C_t^A + P_t^A)$.

In calculating returns from day t to day $t+1$, it is necessary to find straddle pairs that have the same date of maturity and striking prices. Since many straddle pairs satisfy this criterion, the profit or loss from each straddle pair is calculated and the average is taken as a one day return. Again, a practical trading strategy will be to trade options when the price deviation is greater than the transaction costs. Filters with values of 0, 2%, and 5% of market prices are adopted to pick up the large price deviations. Under these filters, the number of days of trading straddles is reduced. To compare the performance of the ISVR and the GARCH methods, the agents can invest in a risk-free asset when no trade happens.

Table 7 reports the averaged return from trading straddles with and without transaction costs. Before transaction costs, the annualized return is 257.81% for the ISVR method, and 230.48% for the ISVR method, with Sharpe ratio of 3.34 and 2.88, respectively. This shows that the average trading profits are significantly greater than zero under both the ISVR and the GARCH methods. The returns from the ISVR method are greater than from the GARCH method for all three filters. For example, with a 5% filter, the ISVR method earns an average return of 316.76%, whereas the GARCH method makes 266.16%.

After accounting for transaction costs equal to 1% of the straddle prices, profits become negative regardless of the filter rule, for both the ISVR or the GARCH methods. The net returns from straddles trading after transaction cost of 1% per straddle is calculated as

$$NAR_{B,t+1} = n_s \cdot \{[(C_{t+1}^A - C_t^A) + (P_{t+1}^A - P_t^A)] - 0.01 \cdot [(C_{t+1}^A + C_t^A) + (P_{t+1}^A + P_t^A)]\} \quad (23)$$

5.3 Asset Class Factor Model and Abnormal Returns

Following Sharpe's (1992) "style regression", an asset class factor model is adopted to evaluate the performance of the volatility trading strategies and analyze their relation with capital market. The asset class factor model can be expressed as:

$$R_t = \alpha + \sum_k \beta_k F_{k,t} + \epsilon_t \quad (24)$$

where R_t is the daily trading returns of the strategies, before filters and transaction costs. $F_{k,t}$ are the factor returns for each asset class. The asset class used are: the S&P 500 index, MSCI world equity index, J.P. Morgan Germany government bond index, J.P. Morgan U.S. government bond index, Goldman Sachs commodity index (GSCI).

Regression results for four volatility trading strategies are reported in Table 8. For the two Delta-neutral trading strategies, Delta-ISVR, Delta-GARCH, the only factors that are significant are the Germany government bond index and U.S. government bond index. With adjusted R^2 of 9.9% and 14.5%, respectively. For the straddle trading strategies, none of the asset class factor is significant, the adjusted R^2 is less than 1%. In particular, none of the four strategies are significantly correlated with the benchmark of the U.S. stock market, S&P 500 index.

The intercept term, α, of the regression is generally treated as the measure of abnormal return, which is the unexplained return by the asset class factor model. All the α of the regressions are positive, with straddle trading strategies significant at 1% significance level. The Daily unexplained return is 0.7% for the Straddle-ISVR, and 0.8% for the Straddle-GARCH method.

Overall, the four dynamic volatility trading strategies offered better risk-return tradeoff: higher Sharpe ratio, lower market risk, and higher abnormal returns. These results are consistent with recent study on hedge funds by Fung and Hsieh (1997) and Liang (1998). They find that hedge funds that employ varies trading strategies differ substantially from traditional investment vehicles such as mutual funds. Hedge fund returns have low and sometimes negative correlation with asset correlation with asset class returns.

6 Conclusion

The conditional volatility of the dollar/mark exchange rate can be predicted both with the implied volatility extracted from foreign currency options, and with the GARCH models. The major difference between these two methods is that while the GARCH method uses *ex post* volatility of past returns, the ISVR method uses the implied volatility extracted from the foreign currency options. This paper investigates whether this volatility predictability is large enough to be economically meaningful, in the sense of identifying the existence of abnormal profit opportunities. In an efficient market, after accounting for transaction costs and risk, no trading strategy should earn abnormal returns.

This paper finds that in the absence of commission costs and the bid-ask spreads, both the delta-neutral and the straddle trading strategies yield significant positive economic profits regardless of which volatility prediction method is used. Increasing the value of the filter serves to raise the profitability of the trading strategies. Therefore, traders who can execute the delta-neutral and the straddle trading strategies at the observed transaction prices can lock in significant profits during the period considered here. Furthermore, the agent using the ISVR method earns greater profits than the agent using the GARCH method. This is consistent with Guo (1996), who finds that implied variance dominate the GARCH model in forecasting future realized variance of the foreign exchange rate.

However, for a nonmember of an exchange, especially individual investors who face higher transaction costs, the magnitude of the correctly predicted volatility changes is generally not large enough to generate abnormal risk–adjusted profits. After accounting for transaction costs of 1% of market prices, the economic profits are not significantly different from zero for most trading strategies. The only exception is for the ISVR method with a 5% price filter.

Finally, the dynamic volatility trading strategies offered better risk-return trade-off: higher Sharpe ratio, lower market risk, and higher abnormal returns. Because of the difference in strategies of trading volatility with investing directly with stocks and bonds, and the resulting lack of systematic correlation with returns from these traditional sources, investments in volatility trading strategies provide a powerful tool for portfolio diversification.

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Table 1: **Descriptive Statistics**

This table reports the descriptive statistics of dollar/mark spot exchange rate. The sample period is from January 1989 to December 1992.

Year	Variable	Mean	Standard deviation	Skewness	Excess kurtosis	Min.	Max.
1989	$S(t)$	0.5323	1.9503×10^{-2}	-0.4219	0.4879	0.4905	0.5924
	$log(S(t))$	-0.6313	3.6427×10^{-2}	0.2987	0.3055	-0.7124	-0.5235
	$S(t)/S(t-1)$	1.0002	0.0071	-0.0184	0.7946	0.9776	1.0236
	$log(S(t)/S(t-1))$	3.0698×10^{-3}	0.1121	-4.7414×10^{-2}	0.7559	-0.3598	0.3709
1990	$S(t)$	0.6204	3.1261×10^{-2}	0.5261	-1.2249	0.5806	0.6801
	$log(S(t))$	-0.4787	4.9802×10^{-2}	0.4893	-1.2713	-0.5438	-0.3856
	$S(t)/S(t-1)$	1.0005	0.0058	0.1392	0.7268	0.9804	1.0205
	$log(S(t)/S(t-1))$	7.6377×10^{-3}	9.1294×10^{-2}	-0.1154	0.6843	-0.3151	0.3234
1991	$S(t)$	0.6045	3.8237×10^{-2}	0.6077	-0.7268	0.5448	0.6916
	$log(S(t))$	-0.5054	6.2251×10^{-2}	0.5224	-0.8058	-0.6073	-0.3688
	$S(t)/S(t-1)$	0.9999	0.0083	-0.2201	1.2758	0.9697	1.0238
	$log(S(t)/S(t-1))$	-0.0199×10^{-3}	0.1326	-0.2588	1.2793	-0.4886	0.3733
1992	$S(t)$	0.6424	3.2259×10^{-2}	0.5933	-0.6718	0.5944	0.7192
	$log(S(t))$	-0.4437	4.9574×10^{-2}	0.5215	-0.7697	-0.5203	-0.3297
	$S(t)/S(t-1)$	0.9998	0.0087	-0.4568	1.3976	0.9701	1.0318
	$log(S(t)/S(t-1))$	-3.8247×10^{-3}	0.1386	-0.4949	1.3587	-0.4831	0.4979

Table 2: **Parameter Estimation of GARCH Models**

This table reports estimation of parameters for GARCH models in conditional variance specifications. The GARCH models are from Engle (1982) and Bollerslev (1986). The series studied is the change in the logarithm of the daily dollar/mark exchange rate. The sample period is from 1989 to March 1993. The t-statistics in parentheses are computed using the robust inference procedure of Bollerslev and Wooldridge (1988). The specification of GARCH(1,1) conditional variances are as follows:

$$\begin{aligned} R_t &= \lambda_0 + \epsilon_t \qquad \epsilon_t|\epsilon_{t-1}, \epsilon_{t-2}, ... \sim N(0, h_t^2) \\ GARCH(1,1) \quad h_t^2 &= \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1}^2 \end{aligned}$$

Year	λ_0	α_0	α_1	β_1	Log. Likelihood
1989	0.0031	0.0008	0.079	0.8571	199.14
	(0.465)	(1.168)	(1.822)	(10.131)	
1990	0.0099	0.0006	0.1038	0.8283	254.231
	(1.89)	(1.12)	(1.93)	(8.41)	
1991	0.0047	0.011	0.299	0.809	160.8
	(0.624)	(3.524)	(2.765)	(11.41)	
1992	0.0026	0.0009	0.1188	0.8301	157.382
	(0.355)	(1.46)	(2.33)	(11.69)	
91.1-93.3	0.0013	0.0015	0.0947	0.8191	345.499
	(0.216)	(2.016)	(2.87)	(12.84)	

Table 3: **Summary Statistics of Volatility Measures**

This table reports the mean, the standard deviation (S.D.), the coefficient of variation (C.V.), and the autocorrelations for various volatility measures. $\sigma_{H,t}$ is the historical volatility, $\sigma_{G,t}$ is the 60–day average GARCH(1,1) volatility forecast, $\sigma_{IHW,P}$ and $\sigma_{IHW,C}$ are implied put and call volatilities from the model of Hull and White (1987). The sample period is from January 1991 through March 1993.

	$\sigma_{H,t}$	$\sigma_{G,t}$	$\sigma_{IHW,P}$	$\Delta\sigma_{IHW,P}$	$\sigma_{IHW,C}$	$\Delta\sigma_{IHW,C}$
Mean	0.114	0.132	0.125	-0.12$\times10^{-4}$	0.126	-0.118 $\times10^{-5}$
S.D.	0.008	0.0075	0.022	0.011	0.018	0.0065
C.V.	0.07	0.057	0.171		0.145	
ρ_1	0.992	0.92	0.878	-0.247	0.938	-0.161
ρ_2	0.981	0.827	0.816	-0.008	0.897	-0.101
ρ_3	0.968	0.743	0.756	-0.036	0.868	-0.010
ρ_4	0.952	0.655	0.704	-0.062	0.84	-0.01
ρ_5	0.934	0.581	0.668	-0.024	0.813	-0.033
ρ_8	0.877	0.465	0.587	-0.053	0.714	-0.051
ρ_{12}	0.786	0.343	0.514	-0.221	0.667	0.046
ρ_{16}	0.677	0.289	0.513	0.054	0.599	0.049
ρ_{20}	0.557	0.184	0.427	-0.029	0.485	-0.004
ρ_{24}	0.430	0.143	0.356	-0.027	0.386	-0.036
Unit Root Test Stat.	-0.299	-3.26	-3.44	-5.72	-3.57	-5.96

Table 4: **Dynamic Properties of the Implied Call and Put Volatilities**

This table reports regressions of the changes in implied call and put volatilities on information variables, such as the include lagged implied volatilities for call and put options, lagged values of interest rate differentials, contemporaneous and lagged changes of exchange rates. The implied call and put volatilities are extracted from the model of Hull and White (1987). The sample period is from January 4, 1991 to March 25, 1993. The interest rate differential is the day-to-day difference of the 90-day domestic and foreign T-bill rates. All t-statistics are based on White (1980) heteroscedasticity-consistent standard errors. Out-of-sample correct prediction is the percentage of times that the sign of volatility changes being correctly predicted.

	Chg. in Put VAR		Chg. in Call VAR	
Variables	Coefficient	t–ratio	Coefficient	t–ratio
Intercept	–0.0017	–2.45	–0.002	–3.96
Monday	0.0018	1.58	0.00072	1.04
Friday	–0.0026	–2.32	–0.0008	–1.21
Chg. Implied Put volatility (t–1)	–0.318	–7.123	0.142	5.33
Chg. Implied Put volatility (t–2)	–0.133	–2.76	0.073	2.54
Chg. Implied Put volatility (t–3)	–0.09	–2.04	0.025	0.94
Chg. Implied Call volatility (t–1)	0.22	3.02	–0.27	–6.18
Chg. Implied Call volatility (t–2)	0.089	1.19	–0.22	–4.98
Chg. Implied Call volatility (t–3)	0.08	1.12	–0.093	–2.18
Log. Spot Rate Chg. (t)	–0.003	–0.87	–0.003	–1.61
Log. Spot Rate Chg. (t–1)	0.0006	0.294	0.0006	0.29
Log. Spot Rate Chg. (t–2)	0.003	0.89	–0.004	–2.01
Abs. Log. Spot Chg. (t)	0.019	1.82	0.017	1.57
Chg. Interest Rate Diff. (t)	0.0034	0.705	0.002	0.72
Chg. Interest Rate Diff. (t–1)	0.003	0.6116	–0.0024	–0.83
Sample Size (days)	510		510	
$\bar{R}^2$	0.255		0.185	
Durbin-Watson	2.05		2.01	
Likelihood Value	1739.58		2020.4	
AIC–LOG	–9.18		–10.224	
SCHWARZ–LOG	–9.07		–10.105	
Out-of-sample correct direction	67.5%		63.3%	

Table 5: **Out-of-Sample Comparison of the Actual and Predicted Option Prices**

This table reports the out-of-sample tests for the actual and predicted option prices. The time t volatility is predicted by the Implied Stochastic Volatility Regression (ISVR) model and the GARCH(1,1) model. The implied stochastic volatilities are estimated from the model of Hull and White (1987). The average GARCH variance forecast is based on the GARCH models of Engle (1982) and Bollerslev (1986). The Wald statistic is for the joint test of $H_0 : \alpha_0 = 0, \alpha_1 = 1$, and the t-statistics are reported in each parentheses. The sample period is from January 4, 1991 to March 25, 1993.

Summary Statistics of the Actual and Predicted Option Prices

	Type	Observation	Mean	Std.
Market	Call	227,589	0.675×10^{-2}	0.416×10^{-2}
ISVR	Call	227,589	0.685×10^{-2}	0.417×10^{-2}
GARCH	Call	227,589	0.704×10^{-2}	0.402×10^{-2}
Market	Put	409,892	0.908×10^{-2}	0.653×10^{-2}
ISVR	Put	409,892	0.935×10^{-2}	0.692×10^{-2}
GARCH	Put	409,892	0.914×10^{-2}	0.616×10^{-2}

$$\text{Market Price}_t = \alpha_0 + \alpha_1 \text{ Model Price}_t + \epsilon_t$$

Call Options (227,589 observations)

Volatility	α_0	α_1	$\bar{R}^2$	Wald statistic
ISVR	0.204×10^{-4}	0.9824	0.9677	427.1
	(6.77)	(2612.7)		
GARCH	-0.122×10^{-3}	0.9759	0.8863	554.3
	(-20.55)	(1332.4)		

Put Options (409,892 observations)

Volatility	α_0	α_1	$\bar{R}^2$	Wald statistic
ISVR	0.441×10^{-3}	0.9239	0.9600	956.3
	(126.96)	(3100.3)		
GARCH	-0.205×10^{-3}	1.0152	0.9163	376.7
	(-38.39)	(2092.9)		

Table 6: **Daily Profits for Delta–Neutral Trading Strategies**

This table reports summary statistics of the daily relative returns of delta-neutral trading strategies. The daily volatilities are predicted from the Implied Stochastic Volatility Regression and the GARCH methods. With the prediction of daily volatilities, theoretical option prices are computed and subsequently compared with the market prices. Each strategy is evaluated under the situations of no transaction cost, and with transaction cost. Sharpe ratios are calculated as the excess return over the U.S. Treasury Rate divided by strategies' sample standard deviations of returns. The asset classes used are: the S&P index (SPX), MSCI world equity index (MSCI) for equity markets, J.P. Morgan global bond index (JPMGBI), J.P. Morgan U.S. government bond index (JPMTUS), J.P. Morgan Germany government bond index (JPMUWG), Goldman Sachs commodity index (GSCI). For the same sample period, the annualized return for the 1 year U.S. Treasury Bill Rate is 4.67 %.

				No Transaction Cost		With Transaction Cost	
Filter	No. of days	Option Type	Volatility Forecast	Annum Return (%)	Sharpe	Annum Return (%)	Sharpe
0%	510	call	ISVR	13.92	2.60	–1.52	–2.34
	510	put	ISVR	14.93	3.28	–1.27	–18.61
	510	call	GARCH	10.12	0.94	–5.31	–2.54
	510	put	GARCH	5.06	-0.48	–11.13	–5.04
2%	508	call	ISVR	18.72	3.94	3.54	-0.74
	510	put	ISVR	17.46	3.92	1.77	-1.39
	510	call	GARCH	12.14	1.4	–3.04	–1.99
	510	put	GARCH	6.33	0.09	–9.61	–4.51
5%	496	call	ISVR	27.58	5.92	12.40	1.72
	506	put	ISVR	22.26	4.85	7.08	0.32
	509	call	GARCH	15.69	2.13	0.759	-1.32
	509	put	GARCH	8.10	0.56	–7.34	–3.62
SPX				13.7 %	0.75		
MSCI				5.87 %	0.1		
JPMGBI				9.91 %	0.9		
JPMTUS				10.98 %	1.81		
JPMUWG				8.35 %	0.269		
GSCI				-2.42%	-0.39		

Table 7: **Daily Profits for Straddles Trading Strategies**

This table reports summary statistics of the daily relative returns of straddles trading strategies. The daily volatilities are predicted from the Implied Stochastic Volatility method and the GARCH method. With the prediction of daily volatilities, theoretical option prices are computed and subsequently compared with the market prices. Each strategy is evaluated under the situation of no transaction cost and with transaction cost. Sharpe ratios are calculated as the excess return over the U.S. Treasury Rate divided by strategies' sample standard deviations of returns. The asset classes used are: the S&P 500 index (SPX), MSCI world equity index (MSCI) for equity markets, J.P. Morgan global bond index (JPMGBI), J.P. Morgan U.S. government bond index (JPMTUS), J.P. Morgan Germany government bond index (JPMUWG), Goldman Sachs commodity index (GSCI). For the same sample period, the annualized return for the 1 year U.S. Treasury Bill Rate is 4.67 %.

			No Transaction Cost		With Transaction Cost	
Filter	No. of days	Volatility Forecast	Annum Return (%)	Sharpe	Annum Return Return (%)	Sharpe
0%	502	ISVR	257.81	3.34	–247.69	–3.37
	502	GARCH	230.48	2.88	–273.24	–3.61
2%	486	ISVR	287.41	3.75	–217.83	–2.97
	490	GARCH	239.59	2.94	–265.39	–3.43
5%	485	ISVR	316.76	4.01	–190.01	–2.52
	488	GARCH	266.16	3.25	–239.08	–3.04
SPX			13.7 %	0.75		
MSCI			5.87 %	0.1		
JPMGBI			9.91 %	0.9		
JPMTUS			10.98 %	1.81		
JPMUWG			8.35 %	0.269		
GSCI			-2.42%	-0.39		

Table 8: **Trading Strategies and Asset Class Factor Model**

This table reports regression analysis of the daily returns of four volatility trading strategies with returns of major asset class. The asset classes are: the S&P 500 index (SPX), MSCI world equity index (MSCI), J.P. Morgan Germany government bond index (JPMUWG), J.P. Morgan U.S. government bond index (JPMTUS), Goldman Sachs commodity index (GSCI). The t-statistics are in parentheses.

Strategy	α	SPX	MSCI	JPMUWG	JPMTUS	GSCI	$\bar{R}^2$
Delta-ISVR	0.00014	-0.009	-0.048	0.102	0.187	0.001	9.9 %
	(0.99)	(-0.39)	(-1.91)	(5.93)	(2.82)	(0.08)	
Delta-GARCH	0.00014	-0.0104	-0.04846	0.1039	0.1923	-0.00008	9.24%
	(1.00)	(-0.438)	(-1.903)	(5.975)	(2.874)	(-0.006)	
Straddle-ISVR	0.007	0.529	0.399	-0.018	-0.826	0.346	0.95%
	(2.25)	(1.01)	(0.69)	(-0.05)	(-0.55)	(1.29)	
Straddle-GARCH	0.008	0.347	0.148	-0.225	-0.284	0.192	0.37%
	(2.89)	(0.68)	(0.27)	(-0.6)	(-0.19)	(0.73)	