Hedging with Floor-Traded and E-mini Stock Index Futures

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This study investigates the out-of-sample hedging effectiveness and dynamic hedge ratios of floor-traded and E-mini futures with VAR, ECM, bivariate GARCH, Kalman filter, and Markov regime switching in the S&P500 and Nasdaq-100 markets. The empirical results show that both the floor-traded and E-mini futures can be good instruments to be used as hedge objectives. The correlation coefficient between spot and futures increases and hedge effectiveness goes up when the hedging period is extended. Moreover, the bivariate GARCH and Markov regime switching show a higher HEI performance in short-term and long-term hedging periods, respectively. Furthermore, floor-traded futures with an open outcry system surprisingly do better than E-mini futures contracts. This study proposes meaningful evidence of hedging strategies for investors with different spot index, hedging periods, and trading mechanisms.

Introduction

Over the last few years, more and more stock and futures transactions have shifted from an open outcry system to an electronic trading system. There are many studies that focus on the issue of the relative price discovery role between open outcry and electronic open auctions. Among those, Grunbichler, Longstaff, and Schwartz (1994) found that when futures are traded electronically, the prices lead the

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spot market. Electronic trading, therefore, can reveal more information for market prices.

Although most futures participants have considered replacing the open outcry with electronic trading, the transactions still have a long way to grow. Taking the U.S. as an example, most futures trading is still taken by a floor broker, but in order to attract more customers, the Chicago Mercantile Exchange (CME), one of the world's largest derivatives exchanges, introduced a global electronic trading system (GLOBEX) in 1992. CME launched the first electronic-mini (E-mini) product in September 9, 1997, known as E-mini S&P500. It was the first screen-based contract to trade during regular trading hours on the floor of a United States exchange. The E-mini Nasdaq-100 was launched following this in June 21, 1999. Because the size of the E-mini is only about one-fifth of a floor-traded contract, the advantage is that trading an E-mini does not mean needing a prodigious financial account. Hasbrouck (2002) showed that the E-mini possesses a useful price discovery role on the S&P500 and Nasdaq-100. E-mini S&P500 and E-mini Nasdaq-100 are two of the fastest growing products CME has ever launched.

Both floor-traded and E-mini contracts function with the same objectives; the major difference is that E-mini contracts allow for a smaller position and they are traded electronically by GLOBEX with excellent liquidity and around-the-clock availability. Improving the speed of price discovery, accurate recording in time, and high liquidity with sufficient privacy are the advantages of the E-mini contracts. Because trading with E-mini can be completed in just one or two seconds by GLOBEX, traders can get an immediate response after completing the trade. By contrast, the open outcry system has to be made in a specific place. The commission of trading E-minis is based upon the basis of contract; that is, larger trading volumes have higher costs for every transaction. Therefore, for a smaller investor, trading in E-mini futures will give them a better advantage than they will give big investors. As an institutional investor, however, traditional future contracts will cost less.

For the last several years, most studies about transaction methods mainly focus on the comparison of price discovery between traditional and electronic transactions and the power of revealing the information. In 1982 after index futures had been launched, investors widened their investment ranges, providing a good risk management strategy for a portfolio manager. One of the major functions is to avoid risks that arise owing to price fluctuations in the spot market. Until now, there have been no studies discussing hedge effectiveness under different transaction mechanisms. Therefore, in order to provide investors a more useful hedging suggestion, the comparison between the two different trading mechanisms from the point of view of hedging is the major focus in this study.

Most of the existing studies concerning hedging take mean variance as the major empirical criterion and use OLS to estimate the optimal hedge ratio. Because of the existence of autocorrelation in the spot and futures markets, the estimated hedge ratio usually is misleading. In order to drill the hedge ratio more, we use dynamic methods to estimate the optimal hedge ratio. Traditional econometric models take the residuals of variance as a constant, but in reality most financial data are characterized with high frequency and volatility clusters also commonly are found. That is, the residuals of variance are not constant, as they change with time. Traditional hedge theory adopts a perfect hedging strategy. In contrast, recent studies such as Figlewski (1984), Cecchetti, Cumby, and Figlewski (1988), Gagnon and Lypny (1997), and Yeh and Gannon (2000) are devoted to studying the dynamic hedging strategy and point out that a traditional hedge strategy may not be able to provide the best result to the general public. They consider dynamic hedging to be a more appropriate strategy. Therefore, we not only look at five different hedge models to estimate the hedge ratio, but also add a dynamic idea to make hedging result comparisons among models in order to determine the optimal hedge strategy.

Investors usually take an opposite contract position in the futures market, while taking up floor-traded and E-mini futures, with their spot market position being used as a hedge strategy to reduce risks. To discuss the dynamic hedging effectiveness, we first will adopt the vector autoregressive model (VAR), error correction model (ECM), bivariate generalized autoregressive conditional heteroskedasticity (GARCH), Kalman filter, and Markov regime switching model to minimize the risk in the spot and futures markets to obtain the optimal hedge ratio. In addition, the technique of a moving window will be taken into consideration in each model to investigate if it could increase hedging effectiveness.

Literature Review

As Webb (1987) noted, traders fear high-volatility markets because of the enhanced danger of uncontrollable losses due to sudden price swings. Hedging plays an essential role in investments. Work (1953) showed that hedging is the most important feature of the futures market. Based on the purpose of hedging, Gray and Rutledge (1971) categorized hedge theory into four forms, including risk elimination, profit maximization, risk reduction, and portfolio approach. In discussing hedge theory, Ederington (1979) lists three categories: traditional hedge theory, optimization hedge theory, and variance minimization hedge theory. Because traditional hedge theory deviates from a practical situation, optimization hedge theory is involved in speculative motivation, while fundamental finance takes minimizing risks as ordinary investors' hedging strategy in a financial assumption. Most hedging studies take variance minimization hedge theory as the empirical study. Among those, Cecchetti, Cumby, and Figlewski (1988) adopted risk minimization and maximized expected utility, taking spot and futures prices as a dynamic distribution to estimate the optimal futures hedge strategy. Junkus and Lee (1985) used profit maximization, risk elimination, risk minimization, and utility maximization as the hedging strategy in an empirical study.

Investors usually take an opposite contract position in the futures market with their spot market position as a hedge strategy to reduce risks. Traditional hedge theory takes a 100 percent position to hedge. That is, investors take an equivalent and opposite position in the futures market as they have in the spot market. They assume that prices in the spot market and futures market change with the same direction and same magnitude. A perfect hedging position can eliminate the risk of a price fluctuation in the spot market. The hedge ratio therefore uses the benefits obtained in the futures market to compensate the loss suffered in the spot market.

Several later researchers achieved different empirical results. Ederington (1979), under the assumption of minimizing the variance, took the price differences in the spot market and futures market to run OLS to estimate the hedge ratio and to make a hedging effect comparison in the T-bill and GNMA markets. He found that the optimal hedge ratio is always less than one, which is totally different from the traditional hedge theory. Junkus and Lee (1985) studied hedging strategy when profit maximization, risk elimination, risk minimization, and utility maximization are adopted. He found that the predicted capacity of prices in the spot market, prices in the future market, and base differentials do affect a hedge strategy's success. A hedging strategy also should vary with different hedge objectives and future contracts. Lindahl (1992) studied MMI and S&P500, discovering that the hedge ratio increases as the hedge period grows under the assumption of minimizing the variance.

On the estimation of the hedging ratio, previous studies take the mean-variance criterion with OLS to estimate the optimal hedge ratio, but because of the existence of the autocorrelation in the spot and future markets, the estimated hedge ratio is usually misleading. Baillie and Myers (1991) adopted the bivariate GARCH to estimate the optimal hedge ratio. They found that the resulting optimal hedge ratio varies with time, and its effectiveness is better than those of the OLS constant hedge ratio models. Kroner and Sultan (1993) took foreign exchange futures to hedge the spot and showed that the hedge effectiveness in the bivariate GARCH is better than the others. In addition, after considering transaction costs, the bivariate GARCH still could improve a traditional hedge strategy's effectiveness and increase investor's hedging management capability over a foreign exchange position. Park and Switzer (1995) compared the bivariate GARCH with others in estimating the out-of-sample optimal hedge ratio. They found that the bivariate GARCH model performs better than the others, even after considering the transaction costs. Koutmos and Pericli (1999) compared EC-GARCH with a traditional static regression model for an-inside sample and out-of-sample hedge effectiveness. Empirical results showed that EC-GARCH performs better than the traditional static ones.

Over the last decade, several researchers devoted to studying dynamic hedging strategy have shown that a traditional hedge strategy may not be the best strategy to fit ordinary investor needs. Cecchetti, Cumby, and Figlewski (1988) indicated that in order to look for optimal outcomes, the dynamic relationship between the spot and futures contract should be considered. Hunter and Timme (1992) reach the same conclusion. Gagnon and Lypny (1997), Koutmos and Pericli (1999), and Yeh and Gannon (2000) suggest that the GARCH model outperforms other economic models in hedging effectiveness. Koutmos and Pericli (1999) adopted a cross-hedging comparative dynamic EC-GARCH model and traditional regression statistic hedging model to compare the hedging effect both within and out-of-sample. He found that the dynamic bivariate EC-GARCH model could provide better results. Yeh and Gannon (2000) took transaction cost into account to employ the dynamic hedging model in order to estimate the optimal hedge ratio, and they showed that the GARCH hedge model creates the most profits. In addition, its out-of-sample expected ability seems to capture the short-run arbitrage opportunity.

Diebold (1986), Lamoureux and Lastrapes (1990), and Hamilton and Susmel (1994) argued that the high volatility persistence also may be due to structural changes or regime shifts in the volatility process. Many studies with a regime switching model focus on the behavior of a single series: for example, Hamilton (1989), Marsh (2000), Dueker and Neely (2002), and Fong and See (2002). Fewer research studies have stressed the topic of relationship and hedging, although Sarno and Valente (2000) showed that the regime switching model explains the relationship between spot and futures prices better. Clarida et al. (2003) wrote that the relationship between spot and forward is related to the different regimes. For the part of hedging, Alizadeh and Nomikos (2004) found that regime switching hedging outperforms the alternative hedge model in lowering portfolio risk in the FTSE100 market within sample and out of sample. But in the S&P500 market, the model only performs better within sample. Other research studies point out that it outperforms the GARCH model.

The existing literature shows many different conclusions. Therefore, in this study we adopt four different hedging models to compare their hedging effect. We also utilize dynamic hedging to investigate if it could increase the hedging effect. We then determine the optimal hedging model and strategy and provide investors with the best strategy.

Data and Models

Data

In this study we examine spot indexes and futures contracts through two different transaction mechanisms, including S&P500 and Nasdaq-100. Table 1 provides a basic introduction of the two indexes. Data include S&P500 and Nasdaq-100 index spot, floor-traded futures, and E-mini futures that are taken from Bloomberg's database. All are daily data, and the sample period is from 1999.6.21 to 2004.6.10. As long as one of the data is missing on the same day, all the data on the same day will be deleted. Some 1251 observations are included in this study. We take the daily stock index with the associated stock index futures to compute its daily rate of return. The rate of returns is computed by differentiating the logarithm of the daily stock index and futures index.

$$\Delta R_t = (\ln R_t - \ln R_{t-1}) \times 100, \tag{1}$$

where ΔR_t is the daily return of the spot and futures at time t, and R_t (R_{t-1}) represents the closing prices of the stock index for spot and futures at time t (t - 1), while ln R_t (ln R_{t-1}) is the logarithm closing prices of stock the index for the spot and futures at time t (t - 1).

Table 1—Basic Introduction of S&P500 and Nasdaq-100 Index Futures Contracts

S&P 500	Floor-Traded Futures	E-mini Futures
Trading Market	CME	CME
Value of Contract	$250 × S&P500 index	$50 × S&P500 index
Month of Contract	3, 6, 9, 12	3, 6, 9, 12
Trading Hours	Floor: 8:30 a.m.- 3:15 p.m. GLOBEX: remaining time	Virtually 24-hour trading (GLOBEX)
Min. Price Fluctuation	0.10 index point = $25 per contract	0.25 index point = $12.5per contract
Last Trading Day	The day before the third Friday of the contract month	8:30 a.m. (Chicago time) on the third Friday of the contract month
Nasdaq-100	Floor-traded futures	E-mini futures
Trading Market	CME	CME
Value of Contract	$100 × Nasdaq-100 index	$20 × Nasdaq-100 index
Month of Contract	3, 6, 9, 12	3, 6, 9, 12
Trading Hours	Floor: 8:30 a.m.- 3:15 p.m. GLOBEX: remaining time	Virtually 24-hour trading (GLOBEX)
Min. Price Fluctuation	0.50 index point = $50 per contract	0.50 index point = $10 per contract
Last Trading Day	The day before the third Friday of the contract month	8:30 a.m. (Chicago time) on the third Friday of the contract month

Models

Estimation of the Hedging Ratio

Vector Autoregressive Model (VAR)

Empirical studies usually are based upon a prior theory to build a structured econometric model. If the underlying endogenous and exogenous variables are mis-specified, then this leads to a useless conclusion. Sims (1980) therefore proposed the VAR model to determine the dynamic model through the characteristics of the data directly. Sims believed that any economic activities' characteristics can be revealed upon the real data and can become a reduced form of a time series model. The model need not consider the causality relationship among the variables and no prior theory is needed. The model takes every variable as being endogenous and constructs a set of regression system of equations. Every variable takes its own possible lag terms with the other variables as the explanation variables to become a regression equation.

Therefore, the system of equations reveals the relationship among variables as being interactive, but not one-way oriented.

Because of the characteristics of time series data (through the help of appropriate lagged terms), the model can involve all the information among economic variables. Our model can be written as:

$$\Delta s_t = \alpha_s + \sum_{i=1}^{m} \beta_{si} \Delta s_{t-i} + \sum_{j=1}^{n} r_{sj} \Delta f_{t-j} + \varepsilon_{st} \tag{2}$$

$$\Delta f_t = \alpha_f + \sum_{i=1}^{a} \beta_{fi} \Delta s_{t-i} + \sum_{j=1}^{b} r_{fj} \Delta f_{t-j} + \varepsilon_{ft}, \tag{3}$$

where

$$\begin{bmatrix} \varepsilon_{st} \\ \varepsilon_{ft} \end{bmatrix} \Bigg| \Omega_{t-1} \sim N(0\ ,\ H_t),\ \varepsilon_{st} \text{ and } \varepsilon_{ft}$$

are independent bivariate random variables and have the same distribution respectively, $Var(\varepsilon_{st}) = \sigma_s^2$, $Var(\varepsilon_{ft}) = \sigma_f^2$, and $Cov(\varepsilon_{st}, \varepsilon_{ft}) = \sigma_{sf}$. The hedge ratio can be written as:

$$hr = Cov(\varepsilon_{st}, \varepsilon_{ft} | \Omega_{t-1}) / Var(\varepsilon_{ft} | \Omega_{t-1}) = \frac{\sigma_{sf}}{\sigma_f^2}, \tag{4}$$

where Ω_{t-1} is an information set which includes all the applicable information at time $t-1$.

Error Correction Model (ECM)

Nelson and Plosser (1982) considered most economic variables to be nonstationary, and their basic statistic characteristics vary with time. In order to avoid spurious regression identification, first-order differentials are needed. To avoid losing long-run information when dealing with the issue of nonstationary, Engle and Granger (1987) suggested utilizing the cointegration method to illustrate the long-run relationship between variables and resolve the possibility of losing information due to the differential process. They showed that as long as two economic variables are cointegrated (even if the variables are affected by certain factors in the short run and turn into a process of random walks), they will return to the long-run equilibrium through the process of the dynamic short-run adjustment.

Assume x_t and y_t are nonstationary in level, but stationary in the first-order differential time series process; that is, x_t and y_t are $I(1)$. If their linear combination is $I(0)$, then x_t and y_t are cointegrated. Through the help of the short-run dynamic process, the long-run equilibrium could be restored. Hence, based upon the ECM hedging model of Krehbiel and Adkins (1993), the model in this study could therefore be rewritten as:

$$\Delta s_t = \alpha_0 + \alpha_1 \mu_{t-1} + b\Delta f_t + \sum_{i=1}^{m} \delta_i \Delta f_{t-i} + \sum_{j=1}^{n} \theta_i \Delta s_{t-i} + \varepsilon_t , \tag{5}$$

where Δs_t represents the rate of return for the spot market, Δf_t is the rate of return for the futures market, μ_{t-1} is the error correction term, ε_t shows the stationary errors at time t, and b is the hedge ratio.

Bivariate GARCH Model

The bivariate GARCH is applicable when a joint normal distribution exists between spot and futures. After introducing the mean equation with error correction term, $(S_{t-1} - \gamma\ F_{t-1})$, the model becomes a bivariate correction model, as in Engle and Granger (1987). On the other hand, Park and Switzer (1995) showed that when the joint distribution of spot and futures varies with time and generates a different variance, the hedge ratio turns into a dynamic formation. Using the bivariate GARCH model, we can calculate the dynamic hedge ratio. In order to take a time-varying variance and covariance, we parameterize the second-order moments by the fixed coefficient bivariate GARCH(1,1). The mean equation of model can therefore be rewritten as:

$$\Delta s_t = \alpha_0 + \alpha_1 (S_{t-1} - \gamma\ F_{t-1}) + \varepsilon_{st} \tag{6}$$

$$\Delta f_t = \beta_0 + \beta_1 (S_{t-1} - \gamma\ F_{t-1}) + \varepsilon_{ft} , \tag{7}$$

where Δs_t and Δf_t are respectively the rate of return of spot and futures, S_t and F_t represent the logarithm price of spot and futures, and $(S_{t-1} - \gamma\ F_{t-1})$ is the error correction term. The error term is $[\varepsilon_{st} \quad \varepsilon_{ft}]' \mid \Omega_{t-1} \sim N(0\ ,\ H_t)$, where Ω_{t-1} is the information set at time t-1. Here H_t is the conditional covariance matrix. The variance equation is,

$$H_t = \begin{bmatrix} h_{st}^2 & h_{sft} \\ h_{sft} & h_{ft}^2 \end{bmatrix} = \begin{bmatrix} h_{st} & 0 \\ 0 & h_{ft} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} h_{st} & 0 \\ 0 & h_{ft} \end{bmatrix} \tag{8}$$

where $h_{st}^2 = c_s + a_s \varepsilon_{st-1}^2 + b_s h_{st-1}^2$, $h_{ft}^2 = c_f + a_f \varepsilon_{ft-1}^2 + b_f h_{ft-1}^2$, and ρ is the fixed correlation coefficient.

Using the maximum likelihood estimation (MLE) and the above model, the dynamic hedge ratio (hr) can be written as:

$$hr_t = \frac{h_{sft}}{h_{ft}^2} , \tag{9}$$

The conditional covariance h_{sft} and conditional variance h_{ft}^2 vary with the newly-revealed information. The estimated hedge ratio will change with time also.

Kalman Filter

The Kalman filter (1960) not only estimates the parameters on level, but also considers the transformation of the state vector space. The major characteristic is its stepwise information updating process, which also illustrates the dynamic relationships between explanatory and dependent variables. In this study we take the Kalman filter with time varying in our model as follows. The observation equation can be written as:

$$\Delta s_t = \alpha_t + \beta_t \Delta f_t + w_t, \tag{10}$$

where Δs_t is the $\rho \times 1$ observed vector, β_t is endogenous and unobserved of the $k \times 1$ state vector, Δf_t is the $\rho \times k$ design matrix, which shows the relationship between Δs_t and β_t, and w_t are the errors with $E(w_t) = 0$, and $E(w_t w_t') = \sigma_w^2$.

The state equation is:

$$\beta_t = \phi(\beta_{t-1} - \bar{\beta}) + \bar{\beta} + v_{t-1}, \tag{11}$$

where ϕ is the $\rho \times k$ design matrix which shows the relationship between β_t and β_{t-1}, v_t are errors with $E(v_t) = 0$ and $E(v_t v_t') = \sigma^2 I$, and β_t is the state vector at time t. Because β_t cannot be observed directly, the optimal estimated output value at time t therefore can be used to derive a predicted output value at time t+1, which also must minimize the predicted error variance $P_{t|t-1}$. Applying equations (9) and (10) into the hedge model, β_t becomes the hedge ratio in terms of state with the characterization of time varying.

Markov Regime Switching

Taking a simple case in this study, we assume that the hedge ratios are different in two unobservable states (regimes). In other words, the relationship between spot and futures markets is different in the two regimes. The equation can be written as,

$$\Delta s_t = \alpha_{i_t} + \beta_{i_t} \Delta f_t + \varepsilon_{t,i_t}, \tag{12}$$

where $\varepsilon_{t,i_t} \sim N(0, \sigma_{i_t}^2)$ for $i_t = 1, 2$ indicates regime 1 and regime 2, respectively. The density function of Δs_t in each regime is:

$$f(\Delta s_t \mid i_t, \Omega_{t-1}) = \frac{1}{\sqrt{2\pi \cdot \sigma_{i_t}^2}} \exp\left[-\frac{(\Delta s_t - \alpha_{i_t} - \beta_{i_t} \Delta f_t)^2}{2\,\sigma_{i_t}^2} \right] \tag{13}$$

and the joint density is:

$$f(\Delta s_t \mid \Omega_{t-1}) = \sum_{i_t=1}^{2} f(\Delta s_t \mid i_t, \Omega_{t-1}) \cdot \Pr(i_t \mid \Omega_{t-1}), \tag{14}$$

where $\Pr(i_t \mid \Omega_{t-1})$ is the conditional regime probabilities in a given state.

We also set $\Pr(i_t = 1 | \Omega_{t-1}) = \pi_{1,t}$ and $\Pr(i_t = 2 | \Omega_{t-1}) = \pi_{2,t}$. The log-likelihood of the above density function can be defined as

$$L = \sum_{t=1}^{T} \log f(\Delta s_t | \Omega_{t-1}) \tag{15}$$

where T represents observations. Therefore, the average hedge ratio (hr) is weighted according to the respective probabilities. The equation can be written as

$$hr_t = \beta_{1,t}\pi_{1,t} + \beta_{2,t}\pi_{2,t} \,. \tag{16}$$

The Hedging Performance

The variance's reduction of the predicted returns in an unhedged spot portion can be used to evaluate hedging performance. That is, the greater the reduction is, the better the hedge performance will be. By the hedge ratio (hr), we can derive the rate of return for the hedge investment combination, which can be written as follows:

$$X_t = \Delta s_t - hr_t \Delta f_t \,, \tag{17}$$

where Δs_t and Δf_t are the daily fluctuation rates of spot and futures markets, respectively, and X_t is the rate of return for the hedge investment combination under the assumption of a short hedge position. The variance of the return for the unhedged asset combination can be expressed as:

$$\mathrm{Var}(U) = \sigma_u^2 = \mathrm{Var}(\Delta s_t) \,. \tag{18}$$

The variance of return for the hedged asset combination is

$$\mathrm{Var}(H) = \sigma_h^2 = \mathrm{Var}(X_t) \,. \tag{19}$$

The hedge performance can be evaluated by equation (20), hedging effectiveness (HE). In order to compute the average hedging effectiveness, the method of a moving window has been adopted. The overall hedging effectiveness can be evaluated by the hedging effectiveness index (HEI), which can be expressed by equation (21), where M is the number of rolling MISSING WORD?. The higher the HEI is, the better the dynamic hedge performance is.

$$HE = \frac{\mathrm{Var}(U) - \mathrm{Var}(H)}{\mathrm{Var}(U)} = \frac{\sigma_u^2 - \sigma_h^2}{\sigma_u^2} \tag{20}$$

$$HEI = \frac{\sum_{j=1}^{M} HE^{(j)}}{M} \,. \tag{21}$$

Empirical Results
Descriptive Statistics

Table 2 contains statistics for the spot index, floor-traded futures, and E-mini futures. Because index futures are the derivatives of the spot index, the statistics for the spot and futures should be closely correlated. From the part of S&P500 in Table 2, we find that the means are similar, but the futures market fluctuated more than the spot did, while the E-mini futures fluctuated more than floor-traded futures did. Unlike S&P500 index, the standard deviation of Nasdaq-100 spot is higher than floor-traded and E-mini futures. All the spot and futures markets present fat tails. Through the Jarque-Beta normality test, we find that all the indexes reject the null hypothesis of normal distribution. Figure 1 presents the trend of three series in each index; the three series are consistent in the latest sample period.

Table 2—Descriptive Statistics

	Mean	S.D.	Skewness	Kurtosis	Min.	Max.	JB
S&P 500							
Spot Index	-0.0137%	1.7049	0.1283	1.5078	-6.0045%	5.5732%	121.8464***
Floor-traded Futures	-0.0143%	1.7345	0.0743	1.5743	-6.2708%	5.7548%	130.2474***
E-mini Futures	-0.0143%	1.7857	0.1422**	1.9741	-6.2708%	6.9804%	207.1914***
Nasdaq-100							
Spot Index	-0.0341%	2.7418	0.2757	2.2200	-10.3089%	17.2029%	272.5438***
Floor-traded Futures	-0.0349%	2.7014	0.1263	2.0546	-10.8153%	15.4447%	223.2047***
E-mini Futures	-0.0349%	2.7139	0.1426	2.0760	-10.8153%	15.4447%	228.7055***

Note: *, **, and *** represent 10 percent, 5 percent, and 1 percent significant levels, respectively. JB represents the statistics of the Jarque-Bera normality test and the null hypothesis is normal distribution. Kurtosis values have been subtracted by three

Unit Root, Cointegration, and ARCH Tests
Unit Root Test

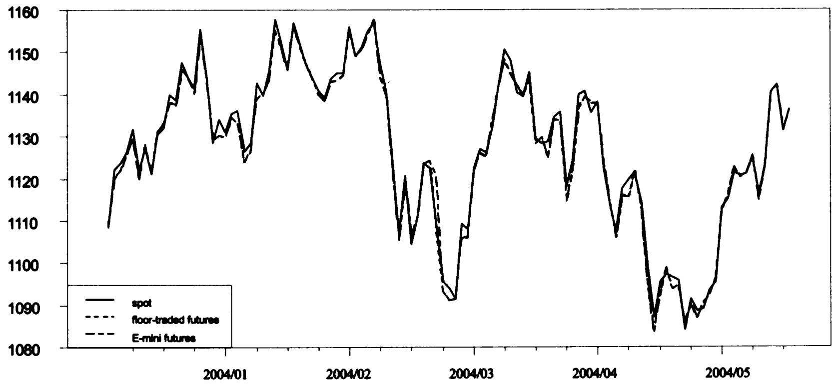
In order to prevent spurious regression and cointegration problems, it is necessary to verify stationary before doing any further analysis. Here, we adopt the augmented Dickey-Fuller (ADF) test to perform the unit root test. In Table 3 we find that all the level terms of spot and futures series cannot reject the null hypothesis of unit root. In other words, the level term series are nonstationary. After a first differential process, however, all series reject the nonstationary hypothesis under 1 percent levels. That is, all these series follow the I(1) process.

Cointegration Test

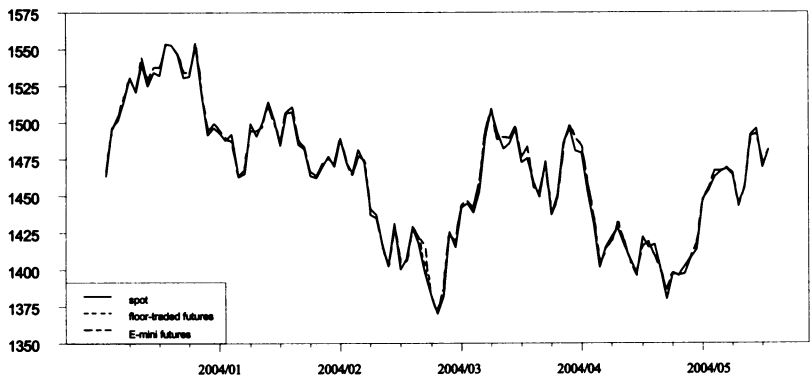
Before constructing the VAR and error correction model, it is necessary to determine the optimal lag terms. In this study the general Akaike information criterion (AIC) is adopted, and the one period lag will be chosen. According to the Johansen maximum likelihood method, which contains the maximum eigenvalue

Figure 1—The Trend of Spot Index, Floor-traded Futures, and E-mini Futures.

The S&P500 Market



The Nasdaq-100 Market



(L-max) and trace test, the long-term relationship between spot and futures will be examined. In Table 4 the same conclusions appear in the S&P500 and Nasdaq-100 indexes. All of the results show that the null hypothesis of a zero cointegration relationship is not significant, but the hypothesis of one cointegration relationship is rejected significantly either in the L-max or trace test. This means that the long-term relationships exist between spot and futures in these two markets.

ARCH Test

We must examine the residuals of equations (6) and (7) before applying the GARCH model. The Lagrange multiplier (LM) test is used to verify the ARCH effect, and the results are reported in Table 5. If the statistical values are significant, then we can say with confidence that the ARCH effects exist. All the outcomes are

Table 3—ADF Unit Root Test

	Constant with Trend		Constant Only	
	Lag	Statistics	Lag	Statistics
Level Term				
S&P500 Stock Index	0	-1.6734	0	-1.5097
Floor-traded Futures	0	-1.6706	0	-1.5068
E-mini Futures	0	-1.7058	0	-1.5234
Nasdaq-100 Stock Index	0	-1.2901	0	-1.0275
Floor-traded Futures	0	-1.2579	0	-1.0063
E-mini Futures	0	-1.2622	0	-1.0093
First Difference				
S&P500 Stock Index	0	-35.8639***	0	-35.8703***
Floor-traded Futures	0	-22.0962***	0	-22.0958***
E-mini Futures	0	-22.2426***	0	-22.2423***
Nasdaq-100 Stock Index	1	-8.9582***	1	-8.9582***
Floor-traded Futures	1	-9.1169***	1	-9.1168***
E-mini Futures	1	-9.1110***	1	-9.1109***

Note: *, **, and *** represent 10 percent, 5 percent, and 1 percent significant levels, respectively. Critical value refers to Dickey-Fuller (1981)

significant under the 1 percent level (no matter in S&P500 or in Nasdaq-100); that is, ARCH effects obviously exist.

Hedge Ratio and Hedging Effectiveness

Benet (1992) studied foreign currency futures and suggested that using out of samples or ex-ante to evaluate hedging effectiveness would be more meaningful for investors. Hence, we adopt Benet's suggestion to evaluate hedging performance out-of-sample results. The estimated time expansion is 800 days. Utilizing the form of a moving window to analyze the effect of the length of hedging periods to the hedging performance in different economic models, we take two, four, eight, twelve, 24, and 48 weeks as the hedging periods in this study and perform daily rolling to hedge. Taking two weeks as an example, as shown on Figure 2, the first loop uses the first

Table 4—Cointegration Tests

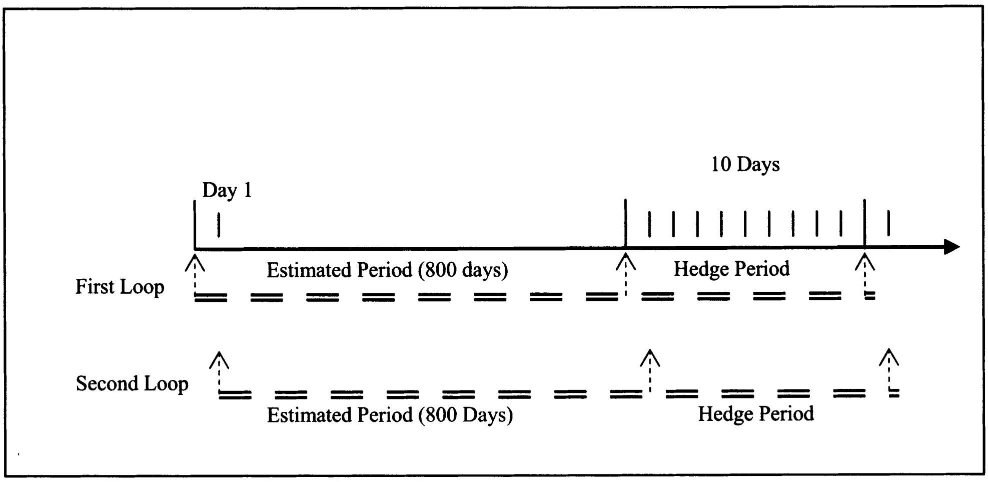
	Eigenvalue	L-max	Trace	H_0: r	Critical Value of L-max	Critical Value of Trace
S&P500						
Spot and Floor-traded Futures	0.0619	79.70	81.86	0	10.29	17.79
	0.0017	2.17	2.17	1	7.50	7.50
Spot and E-mini Futures	0.0740	95.99	98.16	0	10.29	17.79
	0.0017	2.17	2.17	1	7.50	7.50
Nasdaq-100						
Spot and Floor-traded Futures	0.1038	136.80	137.91	0	10.29	17.79
	0.0009	1.11	1.11	1	7.50	7.50
Spot and E-mini Futures	0.1139	150.97	152.08	0	10.29	17.79
	0.0009	1.11	1.11	1	7.50	7.50

Table 5—ARCH Effects

	S&P500		Nasdaq-100	
	Floor-traded Futures	E-mini Futures	Floor-traded Futures	E-mini Futures
ε_{st} for Q(20)	27.7598	28.5366*	53.1721***	53.7102***
ε_{st}^2 for $Q^2(20)$	392.7675***	391.0617***	554.4713***	550.6283***
ε_{st} for LM test	140.6672***	141.3418***	185.5720***	182.9177***
ε_{ft} for Q(20)	27.0494	28.0538	44.3821***	46.1848***
ε_{ft}^2 for $Q^2(20)$	398.7573***	367.7594***	555.8979***	549.6504***
ε_{ft} for LM test	147.1744***	133.1536***	164.0668***	162.2235***

Note: *, **, and *** represent 10 percent, 5 percent, and 1 percent significant levels, respectively

Figure 2–Dynamic Hedging Process 800 Day Time Expansion and 10 Day Moving Window



800 days' spot and futures markets to estimate the hedge ratio and then performs hedging for the next two weeks (ten days). At the end of the ten days, the hedging performance is evaluated and so on. In this study we take five methods, including VAR, ECM, bivariate GARCH(1,1), Kalman filter, and Markov regime switching, to evaluate the dynamic hedging process clearly and completely

In order to obtain the out-of-sample empirical results, we use the latest information to estimate the next period's hedge ratio. Therefore, the entire hedging ratio we derive is a dynamic process, not a constant hedging ratio. Table 6 presents the hedging ratio for all possible combinations. It is found that most hedge ratios are less than one, especially for the S&P500 index. The results are consistent with the studies of Ederington (1979), Junkus and Lee (1985), Lindahl (1992), Park and Switzer (1995), and Holmes (1996). This implies that it is not necessary to take up 100 percent hedging of a futures position for a long spot position. This can reduce the hedging cost for investors. It is worth noting that the hedge ratio estimated by the GARCH model on Nasdaq-100 is higher than others, and the ratio is close to one. This result supports the perfect hedging strategy in the Nasdaq-100 market.

Table 6—The Hedge Ratios of Different Instruments in Various Models

	Period	ECM	VAR	GARCH	Kalman Filter	Regime Switching
S&P500						
Floor-traded Futures	2 weeks	0.9713	0.9724	0.9730	0.9835	0.9714
	4 weeks	0.9501	0.9727	0.9627	0.9849	0.9711
	8 weeks	0.9540	0.9722	0.9925	0.9916	0.9705
	12 weeks	0.9549	0.9697	0.9967	0.9917	0.9699
	24 weeks	0.9560	0.9569	1.0214	0.9944	0.9680
	48 weeks	0.9611	0.9584	0.9906	0.9928	0.9639
E-mini Futures	2 weeks	0.9373	0.9530	0.9937	0.9819	0.9629
	4 weeks	0.9419	0.9532	0.9510	0.9832	0.9626
	8 weeks	0.9441	0.9532	0.9899	0.9899	0.9621
	12 weeks	0.9439	0.9519	0.9898	0.9913	0.9623
	24 weeks	0.9461	0.9415	1.0061	0.9890	0.9604
	48 weeks	0.9513	0.9445	0.9317	0.9878	0.9562
Nasdaq-100						
Floor-traded Futures	2 weeks	0.9910	0.9893	1.0249	0.9726	0.9998
	4 weeks	0.9905	0.9899	1.0202	0.9696	0.9998
	8 weeks	0.9974	0.9978	1.0009	0.9715	0.9998
	12 weeks	0.9992	1.0050	1.0144	0.9722	0.9998
	24 weeks	0.9866	0.9814	1.0092	0.9623	0.9991
	48 weeks	0.9951	0.9895	1.0165	0.9826	0.9950
E-mini Futures	2 weeks	0.9857	0.9819	1.0250	0.9819	0.9985
	4 weeks	0.9853	0.9824	1.0172	0.9832	0.9987
	8 weeks	0.9923	0.9908	0.9976	0.9899	0.9986
	12 weeks	0.9944	0.9989	1.0002	0.9913	0.9986
	24 weeks	0.9842	0.9788	1.0056	0.9890	0.9972
	48 weeks	0.9931	0.9866	0.9926	0.9878	0.9930

Comparing the various models, we calculate all possible HEIs with the moving window method. The results are reported in Table 7. The HEI are positive under each model and hedging period, indicating that the variance of a hedged portfolio is lower than that of an unhedged portfolio. We find that regardless of whether we take floor-traded or E-mini futures, the bivariate GARCH and Markov regime switching have higher HEI performances, while the Kalman filter is the lowest on average.

In Table 7, the GARCH model seems to perform better for two weeks, a short-term hedging period. For the S&P500, the HEIs of hedging with floor-traded and E-mini futures are 0.9452 and 0.9385. For the Nasdaq-100 the HEIs are 0.9425 and 0.9357, respectively. The value is relatively close, but higher than under regime switching. Taking a further look into longer periods, we find that almost all regime switching have higher HEIs in these two markets. This implies that the GARCH model can capture the short-run dynamic effect, and this is consistent with the studies of Yen and Gannon (2000), who suggest that the performance of GARCH model appears on average to persist over a five-day horizon.

Unlike regime switching, the GARCH model assumes that the data follow the unique distribution with the same mean and standard deviation. As the hedging period gets longer, the estimation may misspecify while the regime changes. The regime switching model outperforms the other models with out-of-sample results and a longer hedging period in both S&P500 and Nasdaq-100 markets. The forecasting results in Fong and See (2002) show that the regime switching model performs better in the out-of-sample horizon. Nevertheless, these findings are slightly different from Alizadeh and Nomikos (2004), who argue that the regime switching model outperforms only within a sample in the S&P500 market. We propose another conclusion in the S&P500 market. We find that even though regime switching may be a systematic feature of the data, regime switching may underperform non-regime switching models in the short term and with out-of-sample forecasts resulting from the over-parameterization problem. The assumption of two unobservable regimes is suitable in the long term, however, and the regime switching model performs better than do alternative models.

Table 7—The HEI of Different Instruments in Various Models

	Period	ECM	VAR	GARCH	Kalman Filter	Regime Switching
S&P500						
Floor-traded Futures	2 weeks	0.9442	0.9442	0.9452	0.9314	0.9451
	4 weeks	0.9501	0.9500	0.9511	0.9402	0.9518
	8 weeks	0.9540	0.9540	0.9553	0.9498	0.9555
	12 weeks	0.9549	0.9549	0.9562	0.9477	0.9570
	24 weeks	0.9560	0.9560	0.9576	0.9522	0.9597
	48 weeks	0.9611	0.9609	0.9627	0.9557	0.9641
E-mini Futures	2 weeks	0.9373	0.9370	0.9385	0.9228	0.9379
	4 weeks	0.9419	0.9417	0.9429	0.9293	0.9431
	8 weeks	0.9441	0.9438	0.9452	0.9381	0.9449
	12 weeks	0.9439	0.9447	0.9450	0.9324	0.9458
	24 weeks	0.9461	0.9457	0.9474	0.9391	0.9483
	48 weeks	0.9513	0.9509	0.9528	0.9506	0.9600
Nasdaq-100						
Floor-traded Futures	2 weeks	0.9412	0.9408	0.9425	0.9343	0.9422
	4 weeks	0.9479	0.9475	0.9486	0.9426	0.9505
	8 weeks	0.9541	0.9536	0.9546	0.9467	0.9553
	12 weeks	0.9560	0.9555	0.9564	0.9526	0.9600
	24 weeks	0.9570	0.9565	0.9570	0.9499	0.9625
	48 weeks	0.9584	0.9579	0.9586	0.9562	0.9670
E-mini Futures	2 weeks	0.9346	0.9341	0.9357	0.9228	0.9356
	4 weeks	0.9410	0.9404	0.9416	0.9293	0.9435
	8 weeks	0.9462	0.9456	0.9467	0.9381	0.9470
	12 weeks	0.9474	0.9468	0.9477	0.9324	0.9514
	24 weeks	0.9488	0.9484	0.9486	0.9391	0.9524
	48 weeks	0.9503	0.9497	0.9497	0.9506	0.9578

Let combine the hedge ratio and the hedging performance in Table 6 and Table 7. In the S&P500 market, the perfect hedging strategy is not appropriate. Investors can lower their portfolio risk with fewer transaction costs, and it is not necessary to take up a 100 percent hedging of a futures position for a long spot position. In the Nasdaq-100 market, aside from the short-term hedging period (two weeks), the results are consistent with S&P500. With the higher hedging effectiveness, however, the optimal hedging ratio is 1.0249 and 1.0250 with floor-traded and E-mini futures, respectively. This indicates that investors will take higher futures position relative to the spot position from the short-term period in order to lower the portfolio risk. These results are useful to investors who prefer short-term hedging periods in the Nasdaq-100 market.

Regardless of the models that have been used, we intend to investigate the relationship between the hedging period and hedging effectiveness. Table 7 shows that the longer the sample period is, the more effective the hedging effectiveness becomes across models. This coincides with the findings of Ederington (1979), Figlewski (1984), and Lindahl (1992). Long-term relationships exist between spot and futures, although even the reverse relationship probably occurs in short-term periods. That is, spot and futures may move in different directions in the short run, and hedging could contrarily cause losses. But in the long run (because spots and futures being highly correlated), bear hedging can reveal its effectiveness. Therefore, as the hedge period is extended, the correlation coefficient between spot and futures increases and hedging effectiveness goes up. As a result, a long period hedging strategy would be the better choice when investors are taking index futures as hedging vehicles.

In terms of hedging objectives, regardless of different hedging periods and hedging models, floor-traded futures with an open outcry system perform better than do E-mini futures contracts. For E-mini futures contracts, the electronic platform enables the transaction to be made regardless of place and time, and there is no huge financial cost for small investors. When there is a big transaction amount, however, the cost is relatively high. This means general investment institutions still rely on floor-traded futures to do business, implying that a larger investment is more sensitive to hedging information than is a small investment. In addition, the transaction cost is also the major factor to influence hedging effectiveness. Because the transaction cost of an E-mini contract is based on the basement of contracts, larger trading volumes have higher costs for every transaction. Because the cost will increase with the transaction amount, the hedging effectiveness is therefore relatively small. Regardless of floor-traded or E-mini futures, the HEI is always greater than 90 percent. Both can be good instruments to be used as hedging objectives in either the S&P500 or the Nasdaq-100 markets. Through a dynamic hedging process, the variances of the investment portfolio can decrease noticeably.

Conclusion

In this study we investigated the out-of-sample hedging effectiveness and hedge ratios of floor-traded and E-mini futures with the VAR, ECM, bivariate GARCH, Kalman filter, and Markov regime switching in the S&P500 and Nasdaq-100 markets. The moving window technique is adopted to analyze the effect of the length of time expansion to the hedging performance in different hedging models. The empirical results show that both the floor-traded or E-mini futures can be good instruments to be used as hedge objectives either in the S&P500 or Nasdaq-100 markets. As the hedging period is extended, the correlation coefficient between spot and futures increases and hedging effectiveness goes up.

Second, the bivariate GARCH and Markov regime switching methods have higher HEI performances in short-term and long-term hedging periods, respectively, while the Kalman filter is the lowest on average. Third, except for the short-term hedging period (two weeks) in the Nasdaq-100 market, we can conclude that a perfect hedging strategy is not appropriate. Investors can lower the portfolio risk with fewer transaction costs, and it is not necessary to take a 100 percent hedging of a futures position for a long spot position. In the Nasdaq-100 market, however, investors will take a higher futures position relative to their spot position in the short-term period in order to lower the portfolio risk. Fourth, floor-traded futures with an open outcry system do better than E-mini futures contracts. The main reason is the higher transaction cost of large trading with E-mini futures relative to floor-traded futures. Finally, this study proposes meaningful evidence of hedging strategies for investors with different spot indexes and hedging periods. All the portfolio risk can be lowered by different strategies.

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