Does an Index Futures Split Enhance Trading Activity and Hedging Effectiveness of the Futures Contract?

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Abstract

Lately, several stock index futures exchanges have experimented with an altered contract design in order to make the contract more attractive and to increase investor accessibility. In 1998, the Swedish futures exchange (OM) split the OMX-index futures contract with a factor 4:1, without altering any other aspect of the futures contract design. This isolated contract redesign enables a ceteris paribus analysis of the effects of a futures split. We investigate whether the futures split affects the futures market trading activity, as well as hedging effectiveness and basis risk of the futures contract. We use a bivariate GARCH framework to jointly model stock index returns and changes in the futures basis, and to obtain conditional measures of hedging efficiency and basis risk. We find significantly increased hedging efficiency and lower relative basis risk following the futures split. We also find evidence of an increased trading volume after the split, whereas the futures bid-ask spread appears to be unaffected by the split. Our results are consistent with the idea that the futures split has enhanced trading activity and hedging effectiveness of the futures contract, without raising the costs of transacting at the futures market.

Key words: Index futures split, trading activity, hedging effectiveness, basis risk, bivariate GARCH

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1. Introduction

Stock index futures exchanges all over the world seldom alter contract specifications such as maturity cycles, methods of settlement, contract sizes, etc. The main reason is that an exchange would be reluctant to tamper with a successful contract design. In fact, Bollen et al. (2003) argue that when changes in contract design actually do occur, they are often a last-resort type of action to attract attention to an unsuccessful contract, where the trading demand is diminishing. However, some examples of contractual design alterations at major futures markets have recently occurred. For example, in 1997, the Chicago Mercantile Exchange reduced the contract size, and simultaneously doubled the minimum tick-size, of the S&P 500 futures contract. Moreover, recently, the Sydney Futures Exchange reduced the size of the Share Price Index (SPI) futures contract with a factor of four, as well as increased the minimum tick size correspondingly. The focus in this study is on the 1998 redesign of the Swedish options and futures exchange (OM), when the OMX index futures contract experienced a 4:1 split, keeping all other aspects of the futures contract design intact.

The primary argument supporting a futures contract split is to increase investor accessibility.[2] Huang and Stoll (1998) argue that a smaller futures contract size would benefit small investors who for various reasons cannot trade in large contract sizes. Hence, Huang and Stoll (1998) predict an increasing trading volume, and a broader investor base, following a futures split. However, Bollen et al. (2003) note that a reduced futures contract size would lead to increased trading costs because commissions and fees normally are quoted on a per contract basis.[3] Likewise, futures market makers might be tempted not to reduce quoted futures bid-ask spreads in accordance with the split, resulting in increased trading costs for individual investors. Karagozoglu et al. (2003) recognize that the issue of an optimal contract size requires a careful consideration of the trade-off between trading activity and transactions costs. Moreover, Huang and Stoll (1998) propose that reducing the futures contract size would smooth its trading, and

[2] When the OM announced the 4:1 split in the OMX index futures, they explicitly stated that the reason was to increase accessibility for investors (source: “OM Statement 5/98 regarding Swedish equity related products”). Likewise, the CME announced the split in S&P 500 futures contract, calling it an “effort to make the contract more easily accessible and liquid” (source: Securities Week, “Comment letters to CFTC raise questions about Merc’s plans to split S&P 500 contract”, v. 24, n. 35, 9/1/97).

[3] At the OM, fixed per-contract trading costs at the exchange were reduced with the split factor for both market makers and individual investors.

reduce the risk value of the contract, making it easier for investors to make small adjustments to their portfolios.[4]

In this study, we investigate whether an index futures split affects the trading activity at the futures market and the hedging efficiency of the futures contract with respect to the underlying index stocks. Concerning hedging efficiency, if, following Huang and Stoll (1998), the futures split is successful in increasing trading volume and making trading at the futures market more smooth, the futures contract would be a relatively more efficient hedging tool after the split than before. We apply the classical portfolio hedging model according to Johnson (1960), Stein (1961) and Ederington (1979), with a constant optimal hedge ratio between the number of futures used to hedge a given position in the stock index, to evaluate hedging effectiveness of the futures contract before and after the split. Furthermore, we use the bivariate GARCH framework of Chen et al. (1999), and jointly model stock index returns and changes in the futures basis. In this model, the optimal hedge ratio is allowed to vary over time, conditional on the available set of information, and is a function of the conditional stock index return variance, the conditional variance of the futures basis, and the conditional correlation coefficient between stock index and futures basis innovations.[5] The conditional variance of the futures basis in the bivariate GARCH model constitutes a measure of basis risk when employing the futures contract for hedging purposes. As such, the lower the basis risk, the better hedging tool the futures contract would be. Hence, we also explicitly investigate whether the futures split affects the basis risk, relative the overall market risk, as measured by conditional stock index variance. If, in accordance with Huang and Stoll (1998), the futures split results in smoother futures trading it would be less risky to hold futures, relative the index stocks, after the split.

Our contributions to previous research are twofold. First, unlike e.g. the split in the S&P 500 futures contract which was combined with an alteration in minimum futures tick size, the OMX-index futures split was imposed without changing any other aspects of the futures contract design. This ceteris paribus change in futures contractual design enables us to focus on effects due to the split per se, without interference of other concurrent changes. This is in contrast to for example Bollen et al. (2003), Chen and Locke (2004), and Karagozoglu et al. (2003), where the

[4] Huang and Stoll (1998) define risk value of a futures contract as the product of the contract value and its volatility.
[5] Several authors jointly model spot and futures returns in a time-varying hedging setting, including e.g. Baillie and Myers (1991), Kroner and Sultan (1991), Park and Switzer (1995), and Brooks et al. (2002). We choose to adopt a simplified version of the model according to Chen et al. (1999) because of the explicit treatment of changes in futures basis and basis risk, and the for our purpose tractable measure of hedging efficiency in the model.

authors investigate the combined effects of the S&P 500 futures split and minimum tick size change on futures bid-ask spreads, trading activity and futures market dynamics.[6] Moreover, as the OM, unlike e.g. the CME, keeps a record of bid and ask quotes, we do not need to estimate the bid-ask spread to analyse the effects of the futures split on the spread.[7] Second, whereas previous studies analyzing a split in a futures contract, including Huang and Stoll (1998), all agree on that the split is motivated by the increased investor accessibility, no previous authors investigate the importance of the split for futures hedging effectiveness and basis risk. The effective use of futures contracts for hedging purposes and the associated risks are clearly important issues for futures markets' participants.

Our results indicate a significantly increased futures hedging efficiency following the futures split. The results are robust against the model choice, whether we use the constant or time-varying hedge ratio model to measure hedging efficiency, and are persistent after controlling for changes in the quoted futures bid-ask spread and futures trading volume. We also find a significantly lower relative basis risk after the futures split than before. These results are consistent with the idea that the futures split has enhanced hedging effectiveness of the futures contract. After the split, the futures contract appears to be a more efficient tool for hedging against movements in the underlying stock index, with a lower basis risk. The results have a straightforward policy implication. When the futures contract size becomes "too large" due to the underlying market rallies or long term growth, the futures exchange should consider a split in order to sustain hedging efficiency.

We find no evidence that the futures split affects the relative futures bid-ask spread. However, the futures trading volume increase significantly as a result of the split in the futures contract. The results are persistent after controlling for futures volatility and interdependence between the bid-ask spread and trading volume, and imply that the split has enhanced the liquidity and attractiveness of the futures contract in terms of investors. We find support for the Huang and Stoll (1998) prediction of a broader investor base following the futures split, and find at the same time no evidence in favour of the caveat issued by Bollen et al. (2003), that investor transaction costs measured by futures bid-ask spreads should increase. Hence, the results of our study are good news for investors in general and hedgers in particular, at the OMX-index futures market.

[6] Indeed, Karagozoglu et al. (2003) note that a reduction in contract size and an increase in the minimum tick size might have offsetting effects on transactions costs and liquidity at the futures market.

The remainder of the study is organised as follows. Section 2 contains a description of the Swedish market for OMX-index futures. In this section we also discuss the regulatory changes made at the Swedish options exchange, and the implications these have for this study. Section 3 presents the data and methodology of this study. Section 4 contains the results of the empirical analysis of futures hedging effectiveness, futures basis risk, futures bid-ask spread and trading volume. The study is ended in section 5 with some concluding remarks.

2. The Swedish market for OMX-index futures contracts

In September 1986 the Swedish exchange for futures, options and other derivatives (OM) introduced the OMX-index. It consists of a value-weighted combination of the 30 most actively traded stocks at the Stockholm Stock Exchange (StSE). The purpose of the introduction was to use the OMX-index as an underlying security for trading in standardised European options and futures contracts. Since the introduction, the market for OMX-derivatives has grown substantially. Presently, it is ranked among the ten largest index futures markets in the world.

All listed derivative securities at OM are traded within a fully computerised system. The trading system consists of a limit order book managed by OM. All trading is conducted via members of the exchange. A member is either an ordinary dealer or a market maker. Thus, the trading environment constitutes a combination of an electronic matching system and a market making system. Market makers are likely to endorse liquidity of the market by posting bid-ask spreads on a continuous basis. Trading based only on a limit order book could exhibit problems with liquidity since the high degree of transparency may adversely affect the willingness of traders to place limit orders to the market. The trading system at the StSE is based on the same kind of limit order book as at OM. However, there are no market makers at the Swedish stock market.

The OMX futures market consists of contracts with different maturities. At any time throughout a calendar year, trading is possible in at least three futures contracts, with up to one, two and three months left to expiration respectively. On the fourth Friday each month, when the exchange is open for trading, one set of contracts expires and a new one with time to expiration equal to three months is initiated. For instance, towards the end of September, the September contracts expire

[7] Bollen et al. (2003), Chen and Locke (2004), and Karagozoglu et al. (2003) all use estimated rather than actual quoted bid-ask spreads in order to analyse the effects of the S&P 500 futures split on futures market liquidity.

and are replaced with the December contracts. At the same time, the October contracts (with a time left to expiration equal to one month) and the November contracts (with a time left to expiration equal to two months) are also listed. In addition to the basic maturity cycle, futures contracts with maturity up to two years exist. These long futures contracts expire in January and are included in the basic maturity cycle when they have less than three months left to expiration. All OMX-index futures are settled in cash at maturity.[8]

On April 27, 1998, the OM decided to split the OMX-index with a factor 4:1. The split in the OMX-index reduced the futures contract size to a fourth of its previous value. Hence, a pre-split position of ten futures contracts would be converted into a corresponding post-split position of 40 contracts. As is argued in Bollen et al. (2003), the primary argument for reducing the contract size in a derivatives market is to enhance investor accessibility. However, the authors also claim that a split in the index might increase trading costs. Further, they support their claim with evidence from the split in S&P 500 index suggesting that brokerage fees, per contract, for the index futures did not change after the split. Consequently, an investor trading the same nominal amount of futures after, as before the split, would have experienced transactions costs of a doubled size. At OM the trading costs per contract were reduced with the same factor as the split, both for market makers and end customers. Hence, the split in the OMX-index is not expected to lead to an increase in overall futures trading costs.[9]

3. Data and methodology

3.1 Data

The study uses a data set, which consists of all futures contracts, with the OMX-index as underlying security, listed at OM. The sample contains daily closing data between October 24, 1994, and June 29, 2001. The data are obtained from OM and includes information of closing futures bid and ask quotes, trading volume (the number of contracts as well as the transacted amount in SEK) and open interest for each contract.

[8] Note however that the OMX-index futures are not settled on a daily basis. Instead, the futures contracts resemble forward type of contracts as they are settled at maturity only.
[9] As a comparison, in conjunction with the S&P 500 futures split, the CME did not reduce exchange fees correspondingly.

The empirical analysis of futures bid-ask spread and trading volume is concentrated to the nearby futures contract, i.e. the futures contract series closest to maturity. Also, when we analyse daily stock index and futures price changes, we use mid-quote futures prices and the nearby contract, except during expiration weeks. Each Thursday before the expiration week, the current futures position is "rolled over" into the next contract. For instance, on Thursday the week prior to the January expiration week, the January futures contract held from Wednesday to Thursday close is sold at the prevailing mid-quote. Then, a new futures position is initiated using the February contract, at the Thursday's mid-quote. This position is held until Friday's close. Thereafter, the February contract is used until the next rollover. If the Friday before the expiration week is a holiday, the rollover is initiated at the close of the corresponding Wednesday.

3.2 Futures hedging and dynamics of stock index returns and futures basis

To investigate the hedging effectiveness of the index futures contract before and after the futures split, we use the dynamic framework according to Chen et al. (1999) to obtain a measure of the optimal futures hedge ratio. Chen et al. (1999) propose a bivariate GARCH model for the development of the stock index returns and the futures basis. Their main purpose is to investigate the Samuelson effect, which refers to increasing futures price volatility as the futures contract approaches the expiration date. Moreover, they apply their model to futures hedging, and present a measure of hedging effectiveness that takes stochastic volatility of both stock index returns and changes in the futures basis into account. We use the Glosten et al. (1993) asymmetric GARCH(1,1) for the joint dynamics, and the constant conditional correlation specification according to Bollerslev (1988).

Using the notation in Chen et al. (1999), we let S_t and F_t denote the stock index and futures price on day t respectively.[10] Furthermore, we define the concurrent futures basis as $B_t = F_t - S_t$.[11] We specify the stock index return dynamics according to the following process:

[10] Note that F_t is the mid-quote futures price on day *t*, i.e. the average of the closing bid and ask quotes.

[11] We use the "raw" basis in the empirical analysis. As a robustness check, we also employ an adjusted basis, where we adjust the futures price with a cost-of-carry correction for the prevailing interest rate and dividend yield. As the subsequent results are similar whether we use the "raw" or adjusted basis, we choose to present the results from the current more simple specification.

(1) $$\frac{\Delta S_t}{S_{t-1}} = a_0 + \sqrt{h_t}\varepsilon_t$$

(2) $$h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 Q_{t-1} \varepsilon_{t-1}^2$$

where ΔS_t denotes the change in the stock index price from day $t-1$ to day t, $\varepsilon_t \middle| \Im_{t-1} \sim N(0,1)$ is a stock index return shock or innovation on day t, $\Im_t$ denotes the information set available on day t, $N(0,1)$ is the standard normal distribution, h_t is the conditional stock index variance on day t, and Q_t is a dummy variable equal to one if $\varepsilon_t > 0$ and zero otherwise.

The development of the futures basis, normalised by the stock index level, is modelled according to:

(3) $$\frac{\Delta B_t}{S_{t-1}} = b_0 m_t + b_1 \frac{B_{t-1}}{S_{t-1}} + \sqrt{q_t}\xi_t$$

(4) $$q_t = \beta_0 + \beta_1 q_{t-1} + \beta_2 \xi_{t-1}^2 + \beta_3 D_{t-1} \xi_{t-1}^2$$

where ΔB_t denotes the change in the futures basis from day $t-1$ to day t, $\xi_t \middle| \Im_{t-1} \sim N(0,1)$ is a corresponding futures basis shock on day t, m_t is the time to maturity in years of the futures contract, q_t is the conditional futures basis variance on day t, and D_t is a dummy variable equal to one if $\xi_t > 0$ and zero otherwise. Following Bollerslev (1988), the conditional correlation coefficient between the two shocks is equal to a constant ρ:

(5) $$Cov_{t-1}(\varepsilon_t, \xi_t) = \rho$$

The bivariate system in equations (1) through (5) describes the dynamic joint development of stock index returns and the futures basis. Accordingly, we can obtain an expression for the conditional variance of futures returns as:

(6) $$Var_{t-1}\left(\frac{\Delta F_t}{F_{t-1}}\right)=\frac{1}{F_{t-1}^2}Var_{t-1}(\Delta F_t)=\frac{1}{F_{t-1}^2}Var_{t-1}(\Delta S_t+\Delta B_t)=$$

$$\frac{S_{t-1}^2}{F_{t-1}^2}Var_{t-1}\left(\frac{\Delta S_t}{S_{t-1}}+\frac{\Delta B_t}{S_{t-1}}\right)=$$

$$\frac{S_{t-1}^2}{F_{t-1}^2}\left[Var_{t-1}\left(\frac{\Delta S_t}{S_{t-1}}\right)+Var_{t-1}\left(\frac{\Delta B_t}{S_{t-1}}\right)+2Cov_{t-1}\left(\frac{\Delta S_t}{S_{t-1}},\frac{\Delta B_t}{S_{t-1}}\right)\right]=$$

$$\frac{S_{t-1}^2}{F_{t-1}^2}(h_t+q_t+2\rho\sqrt{h_t q_t})$$

According to standard portfolio hedging results, see e.g. Johnson (1960), Stein (1961) and Ederington (1979), the optimal hedge ratio must equal the conditional covariance between futures and un-hedged stock index price changes, divided by the conditional variance of the futures price changes. In our framework, using the results from Chen et al. (1999) and the system of equations (1) through (5), the optimal hedge ratio can be written as:

(7) $$\varphi_t=\frac{Cov_{t-1}(\Delta F_t,\Delta S_t)}{Var_{t-1}(\Delta F_t)}=\frac{Cov_{t-1}(\Delta B_t+\Delta S_t,\Delta S_t)}{Var_{t-1}(\Delta B_t+\Delta S_t)}=\frac{Cov_{t-1}\left(\frac{\Delta B_t}{S_{t-1}}+\frac{\Delta S_t}{S_{t-1}},\frac{\Delta S_t}{S_{t-1}}\right)}{Var_{t-1}\left(\frac{\Delta B_t}{S_{t-1}}+\frac{\Delta S_t}{S_{t-1}}\right)}=$$

$$\frac{Cov_{t-1}\left(\frac{\Delta B_t}{S_{t-1}},\frac{\Delta S_t}{S_{t-1}}\right)+Var_{t-1}\left(\frac{\Delta S_t}{S_{t-1}}\right)}{Var_{t-1}\left(\frac{\Delta S_t}{S_{t-1}}\right)+Var_{t-1}\left(\frac{\Delta B_t}{S_{t-1}}\right)+2Cov_{t-1}\left(\frac{\Delta B_t}{S_{t-1}},\frac{\Delta S_t}{S_{t-1}}\right)}=\frac{\rho\sqrt{h_t q_t}+h_t}{h_t+q_t+2\rho\sqrt{h_t q_t}}$$

The optimal hedge ratio φ_t in equation (7) is conditional on the available information, and depends on the conditional variance of stock index returns h_t, the conditional variance of the futures basis q_t, and the conditional correlation coefficient ρ. Hence, in the GARCH framework, the optimal hedge ratio varies over time in accordance with the information flow.

A natural benchmark, building on the classical hedging literature, is to assume a constant hedge ratio at two different levels, before and after the futures split. This can be achieved within the following regression model, where we regress daily stock index returns on daily futures price changes, normalised by the stock index level:

$$\frac{\Delta S_t}{S_{t-1}} = c_{0,b}P_{b,t} + c_{0,a}P_{a,t} + c_{1,b}P_{b,t}\frac{\Delta F_t}{S_{t-1}} + c_{1,a}P_{a,t}\frac{\Delta F_t}{S_{t-1}} + u_t \tag{8}$$

$$u_t = e_t - \sum_{i=1}^{5}\theta_i u_{t-i} \tag{9}$$

$$e_t = \sqrt{g_t}\,\eta_t \tag{10}$$

$$g_t = \gamma_0 + \gamma_1 g_{t-1} + \gamma_2 \eta_{t-1}^2 + \gamma_3 Z_{t-1}\eta_{t-1}^2 \tag{11}$$

where $\eta_t \big| \Im_{t-1} \sim N(0,1)$ is a return shock on day *t*, g_t is the conditional variance on day *t*, and Z_t is a dummy variable equal to one if $\eta_t > 0$ and zero otherwise. Each dummy variable $P_{b,t}$ and $P_{a,t}$ equals one before and after the split respectively. The regression formulation in equations (8), through (11) allows for time-varying volatility according to the Glosten et al. (1993) framework, and for residual autocorrelation up to five lags. The regression coefficient $c_{1,b}$ corresponds to the constant hedge ratio:

$$c_{1,b} = \frac{Cov\left(\frac{\Delta F_t}{S_{t-1}}, \frac{\Delta S_t}{S_{t-1}}\right)}{Var\left(\frac{\Delta S_t}{S_{t-1}}\right)} = \frac{Cov(\Delta F_t, \Delta S_t)}{Var(\Delta F_t)} \tag{12}$$

where *Var*(.) and *Cov*(.) represents an unconditional variance and covariance respectively during the period before the split. The $c_{1,a}$ coefficient in equation (8) has a similar interpretation after the split. In the constant hedge ratio regression model, the regression R^2 is a classical measure of hedging effectiveness.[12] In the regression framework, R^2 measures the proportion of the variance in the stock index returns that can be explained by the normalised futures price changes, or in a hedging situation, eliminated by hedging with futures. Hence, we can write the hedging effectiveness measure in the constant hedge ratio model, for the period before the split, as:

$$x_b = R_b^2 = c_{1,b}^2 \frac{Var(\Delta F_t)}{Var(\Delta S_t)} = \left[\frac{Cov(\Delta F_t, \Delta S_t)}{Var(\Delta F_t)}\right]^2 \frac{Var(\Delta F_t)}{Var(\Delta S_t)} \tag{13}$$

Likewise, we obtain a similar hedging effectiveness measure x_a using the $c_{1,a}$ coefficient and the observations after the split. It is also possible to compare the hedging effectiveness of the futures before and after the split by comparing R^2's or by testing the null hypothesis that $c_{1,b}$ equals $c_{1,a}$ in equation (8).

In the time-varying hedge ratio model according to Chen et al. (1999), where the optimal hedge ratio is expressed in equation (7), we can obtain a measure of hedging effectiveness by considering a time-varying, conditional, version of equation (13) as:

$$x_t = \left[\frac{Cov_{t-1}(\Delta F_t, \Delta S_t)}{Var_{t-1}(\Delta F_t)}\right]^2 \frac{Var_{t-1}(\Delta F_t)}{Var_{t-1}(\Delta S_t)} = \frac{[Cov_{t-1}(\Delta F_t, \Delta S_t)]^2}{Var_{t-1}(\Delta F_t) Var_{t-1}(\Delta S_t)} = \tag{14}$$

$$\frac{(\rho\sqrt{h_t q_t} + h_t)^2}{(h_t + q_t + 2\rho\sqrt{h_t q_t})h_t}$$

In equation (14), x_t constitutes a hedging effectiveness measure, which is conditional on the available information set.[13] Moreover, x_t depends on the conditional variance of stock index returns h_t, the conditional variance of the futures basis q_t, and the conditional correlation coefficient ρ. It is also possible to interpret q_t as a measure of conditional futures basis risk. As such, the less basis risk, i.e. the closer q_t is to zero, the more effective futures hedge can be

[12] See e.g. Ederington (1979).
[13] See Lien (2005) for a similar expression of hedging efficiency in a stochastic volatility framework.

achieved, and the closer x_t is to one in equation (14). In general, the closer x_t is to one, the higher is the percentage risk reduction when the optimal hedge ratio is employed.

3.3 Effects of split on hedging effectiveness, basis risk, futures bid-ask spread and trading volume

In order to investigate whether the futures split has affected the hedging effectiveness of the futures contract, we formulate the following regression model, with x_t as the dependent variable:

(15) $$x_t = \delta_0 + \delta_1 P_{a,t} + \delta_2 SPREAD_t + \delta_3 VOLUME_t + \delta_4 m_t + u_{x,t}$$

where $SPREAD_t$ is the relative bid-ask spread, i.e. absolute closing bid-ask spread divided by the midpoint of the bid and ask quote, of the nearby futures contract on day *t*, $VOLUME_t$ is the natural log of the number of traded nearby futures contracts on day *t*, m_t is the annualised time to maturity of the nearby futures contract, and $u_{x,t}$ is a residual term. As a result of the split, for the same amount of notional trading, the number of futures contracts traded would increase by a factor of four. Hence, we normalise the trading volume after the split to pre-split levels by dividing the post-split volume with four.

The inclusion of the dummy variable $P_{a,t}$ in equation (15), as in equation (8), enables us to test the null hypothesis that hedging effectiveness, as measured by x_t, is unaffected by the split, controlling for futures bid-ask spread, trading volume, and maturity. We use time to maturity of the futures contract as a control variable in the regression according to equation (15), because Chen et al. (1999) find evidence that this variable is important for futures hedging effectiveness. Furthermore, Chen and Locke (2004) find that a futures split affects the futures bid-ask spread and trading volume. Hence, we control for these two variables as well.

We use a similar regression framework as in equation (15) to analyse the futures basis risk before and after the split. We are not interested in the change in futures basis risk per se, rather in whether the basis risk in relation to stock index volatility has changed as a result of the index split. Therefore, we define y_t as the square root of the ratio between q_t and h_t, and regress y_t on the same explanatory variables as in equation (15) according to:

(16) $$y_t = \phi_0 + \phi_1 P_{a,t} + \phi_2 SPREAD_t + \phi_3 VOLUME_t + \phi_4 m_t + u_{y,t}$$

where $u_{y,t}$ is a residual term. The test of the null hypothesis that the relative futures basis risk is unaffected by the futures split boils down to test whether the coefficient ϕ_1 is equal to zero.

In addition, we investigate the impact of the split on the futures bid-ask spread and trading volume. Following the analysis in Chen and Locke (2004), and Bollen et al. (2003), we formulate the following time series model for the futures bid-ask spread:

(17) $$SPREAD_t = \lambda_0 + \lambda_1 P_{a,t} + \lambda_2 FUTVOL_t + \lambda_3 m_t + \lambda_4 VOLUME_t + u_{s,t}$$

where $FUTVOL_t$ is the square root of the conditional variance of the futures returns according to equation (6), and $u_{s,t}$ is a residual term. Likewise, we model the futures trading volume using the following regression:

(18) $$VOLUME_t = \omega_0 + \omega_1 P_{a,t} + \omega_2 FUTVOL_t + \omega_3 m_t + \omega_4 SPREAD_t + u_{v,t}$$

where $u_{v,t}$ is a residual term. Again, we are able to test the impact of the futures split on the bid-ask spread, in equation (17), and trading volume, in equation (18), by testing for significance of the corresponding coefficient associated with the dummy variable $P_{a,t}$. Wang et al. (1997) argue that futures trading volume and bid-ask spreads are jointly determined. Therefore, we treat the dependent variables $SPREAD_t$ and $VOLUME_t$ as endogenous in a simultaneous structural model consisting of the two equations (17) and (18).

4. Empirical results

Table 1 presents estimation results from the bivariate GARCH model for stock index returns and changes in the futures basis. There is strong evidence of conditional heteroskedasticity in both the stock index and the futures basis variance equations. The conditional stock index variance exhibits a high level of persistence (as measured by the sum $\alpha_1 + \alpha_2 + \alpha_3 = 0.8823$ for positive shocks, and $\alpha_1 + \alpha_2 = 0.9888$ for negative shocks). At lag one, the impact of a positive shock corresponds to $\alpha_2 + \alpha_3 = 0.0612$, whereas the impact of a negative shock is $\alpha_2 = 0.1677$. The α_3-coefficient is significantly negative at the one percent level, which suggests a leverage effect in the stock index returns. After the initial impact, a stock index return shock diminishes at a rate of $\alpha_1^k = 0.8211^k$ for lags $k > 1$.

In the conditional futures basis variance equation the parameters are quite similar in magnitude compared to those in the stock index return variance equation. The futures basis variance exhibits a high level of persistence, $\beta_1 + \beta_2 + \beta_3 = 0.8798$ for positive shocks and $\alpha_1 + \alpha_2 = 0.9435$ for negative shocks. Moreover, a positive basis shock has an initial impact of $\beta_2 + \beta_3 = 0.0602$ and a negative shock affects the conditional futures basis variance with a significantly higher impact equal to $\beta_3 = 0.1239$. Also, a futures basis shock diminishes at the rate $\beta_1^k = 0.8196^k$ at lags longer than $k = 1$. In the futures basis mean equation, the b_0-coefficient is significantly positive, implying that changes in futures basis are larger for longer maturities. Furthermore, the b_1-coefficient is significantly negative with an estimated value similar to the one obtained in Chen et al. (1999).

The correlation coefficient between the two conditional shocks is significantly positive at an approximate estimated value of 0.10. In order to make sure that the constant correlation specification is sufficient, we perform the LM test for a constant correlation according to Tse (2000). This results in a test statistic equal to 1.302 (with a *p*-value = 0.2539). The test statistic is approximately chi-square distributed under the null hypothesis of constant correlation. Hence, we cannot reject the null, and are content with the constant correlation specification.

Using the estimated parameters in Table 1, we obtain the conditional futures hedge ratio and conditional hedging effectiveness measure according to equation (7) and (14) respectively. Figure 1 displays these time series over the entire sample period, together with the estimated coefficients $c_{1,b}$ and $c_{1,a}$ from equation (8), which corresponds to the constant hedge ratio before and after the futures split respectively. Evidently, the conditional hedge ratio fluctuates dramatically over the sample period, and appears to be lower more often than above the corresponding constant hedge ratio. Moreover, by a casual glance at Figure 1, the futures hedging effectiveness appears to be higher after the split than before. We also calculate the square root of the ratio between the conditional basis variance and the conditional stock index variance, in order to use as a measure of relative basis risk of the futures contract. Figure 2 displays the basis risk measure over the entire sample period. The two solid horizontal lines represent the average basis risk measure before and after the split respectively. On average, the basis risk appears to be lower after the split compared to before. This observation goes well in line with an increased futures hedging effectiveness following the futures split.

In Table 2, we present the results from the constant hedge ratio model according to equations (8) through (11). The main hypothesis associated with this model to test is whether the hedge ratio is the same before and after the split, or in terms of the regression coefficients, whether $c_{1,b}$ is equal to $c_{1,a}$. According to the results in Table 2 it is possible to reject this hypothesis at the one percent significance level. In fact, after the split, the hedge ratio is significantly larger than before. Note that before the split, the constant hedge ratio estimate equals 0.95, whereas after the split, the corresponding estimate is just above 0.97. Noteworthy is also that the constant hedge ratio is significantly lower than one, both before and after the split. At any reasonable significance level, we can reject each individual null hypothesis that $c_{1,b}$ and $c_{1,a}$ is equal to one respectively. Hence, according to constant hedge ratio model, it is optimal to hedge a 100 percent index stock position with only a 95 percent futures position before the split, and an approximate 97 percent futures position after the split. We also calculate the futures hedging efficiency measure, before and after the split respectively, according to equation (13), as $x_b = 0.9512$ and $x_a = 0.9711$. Given these estimates, and the results from the constant hedge ratio model, we find evidence of a corresponding significant improvement in futures hedging effectiveness following the split.

Table 3 contains some summary statistics for the variables used throughout the empirical analysis. Together with sample mean, median, and standard deviation for each variable, before as well as after the split, Table 3 also encloses results from a unit root test for stationarity of each variable. We use an augmented Dickey-Fuller test (see Fuller, 1996) to test each individual null hypothesis that the time series has a unit root. Using the *p*-values according to MacKinnon (1996), it is possible to reject each null hypothesis of a unit root at the one percent significance level. Hence, all variables used in the empirical analysis can be considered stationary.

From Table 3, the mean (median) of the hedging efficiency measure x_t equals 0.95 (0.95) before the split and 0.96 (0.97) after the split, whereas the corresponding mean (median) of the hedge ratio φ_t equals 0.93 (0.93) before and 0.94 (0.95) after the split. Moreover, the standard deviation of each variable appears to be lower after the split than before. In Table 4, we present the results from a *t*-test and a Wilcoxon rank sum test of the hypothesis of equal variable mean and median respectively during both sub-samples, before and after the split. For both x_t and φ_t, we can reject each null hypothesis of equality. Hence, on average, we observe a significant increase in the conditional hedging efficiency and the conditional hedge ratio following the futures split, which is consistent with the results from the constant hedge ratio model, presented in Table 2.

In Table 3 and 4, we also observe a significant decrease in the mean (median) of the relative conditional basis volatility y_t from 0.24 (0.23) before the split to 0.19 (0.18) after the split. Although we observe a significant increase in mean (median) conditional basis volatility per se from 0.25 (0.24) percent before the split to 0.32 (0.29) percent after the split, our measure of the *relative* basis risk is significantly lower in the post-split sub-sample, as we observe a concurrent significant increase in mean (median) stock index volatility from the pre-split level 1.12 (1.03) percent to the post-split level 1.77 (1.69) percent. According to the definition of conditional futures hedging efficiency in equation (14), we concur that the significant decrease in relative basis risk is compatible with the significant increase in hedging efficiency of the futures contract following the split.

The relative futures bid-ask spread shows an increase from a mean (median) level of 0.11 (0.09) percent before the split to a corresponding post-split level of 0.15 (0.11) percent. Moreover, the mean (median) natural log of futures trading volume shows a concurrent increase from 8.38 (8.39) to 8.71 (8.72). These figures correspond to an increase in average trading volume from approximately 4,360 to 6,060 futures contracts per day, where the trading volume figures are normalised to pre-split levels. According to the test-statistics in Table 4, both the average relative spread increase and the average trading volume increase is significant at any reasonable significance level. Finally, using the results in Table 3 and 4, we find evidence of significantly increased average conditional futures volatility from the pre-split to the post-split sub-sample, which is consistent with the corresponding increase in conditional stock index volatility.

Table 5 contains the results from the regression models with the conditional hedging efficiency and conditional basis risk measures as dependent variables, according to equation (15) and (16) respectively. The regression framework can be considered as a multivariable extension of the *t*-test and Wilcoxon rank sum test in Table 4, that allows for a pre- and post-split comparison of hedging efficiency and basis risk, taking changes in futures bid-ask spread and trading volume, as well as autocorrelation, into account. Each regression model is individually estimated with non-linear least squares, adding residual autocorrelation terms in a stepwise fashion.[14] The regression results confirm the results from Table 4. In the hedging efficiency equation, the coefficient for the post-split dummy variable is significantly positive at the one percent level. Moreover, in the basis risk regression equation, the corresponding dummy variable coefficient is significantly negative, also at the one percent level. At the same time, in each regression equation, none of the control variables futures bid-ask spread, futures trading volume or futures maturity, have coefficients that are significantly different from zero, whereas each regression residuals show a high degree of autocorrelation. The regression results are consistent with that the futures split leads to an improved hedging efficiency, and a reduced relative basis risk, of the futures contract.

Table 6 reports the results from the simultaneous structural model for the futures relative bid-ask spread and trading volume according to equation (17) and (18). We estimate both equations using a non-linear version of the two-stage least squares technique. In each equation, we add autoregressive residual terms in a stepwise analysis to take residual autocorrelation into account. Starting with the results for the bid-ask spread equation; we cannot reject the hypothesis that the split has no effect on the relative bid-ask spread as the coefficient for the post-split dummy variable is not significantly different from zero. As a result, we find no evidence that the futures split affects the relative futures bid-ask spread, after controlling for futures trading volume, futures volatility, maturity, and autocorrelation in the futures spread residuals. This result contradicts Bollen et al. (2003) as well as Chen and Locke (2004) who find evidence of an increased spread after the futures contractual redesign. However, both these studies analyse effects following the redesign of the S&P 500 futures contract, which included a split as well as a change in minimum tick size. Therefore, it might be difficult to isolate the effect of the split on the futures bid-ask spread, as the split coincides with other contractual changes. This is not a problem in this study, wherefore we are able to perform a relatively more "clean" analysis of the

[14] We also estimate the regressions by non-linear two stage least squares, treating the bid-ask spread and trading volume as endogenous variables. As the results are similar, we only present the ones from the single equation individual estimations.

futures split. Moreover, unlike the above cited studies, we analyse actual quoted bid-ask spreads rather than estimated spreads.

We also find a significantly positive relationship between futures volatility and relative bid-ask spread, at any reasonable significance level, and between maturity and the relative spread on the five percent level. These results are reasonable and consistent with previous studies (see e.g. Wang et al., 1997). Moreover, the futures bid-ask spread is not dependent on the concurrent trading volume of the futures contract. In the spread equation, the coefficient for (the instrument for) trading volume is not significantly different from zero.[15]

Turning to the results for the trading volume equation, we note a significantly positive coefficient for the post-split dummy variable at the five percent level. As a result, even after controlling for the futures bid-ask spread, volatility, maturity, and residual autocorrelation, we find evidence that the split has lead to an increase in trading volume. Moreover, futures trading volume is significantly positively related to futures volatility at the one percent level, significantly negatively related to maturity at the five percent level, and significantly positively related to the instrument for the concurrent futures bid-ask spread only at the ten percent level. These results are consistent with previous research (see e.g. Wang et al., 1997), except for the not highly significant, but surprising result of a positive relationship between bid-ask spread and trading volume.

5. Concluding remarks

This study investigates the effects of a futures split on futures market trading activity and the future's hedging efficiency and basis risk. In 1998, the Swedish exchange for options and futures (OM) split the OMX-index futures contract with a factor 4:1, where one old pre-split contract was transformed into four new post-split contracts. In a concurrent news-bulletin, the exchange stated that the intention with the split was to increase investor accessibility to the futures contract. Since the introduction of the OMX-index futures contract in the mid-eighties, the underlying index has soared from the initial level 500 to around 3,000 at the time of the split. The split

[15] In fact, we obtain similar results if we perform a single-equation non-linear least squares estimation of the spread equation, without the volume variable. Nevertheless, we retain the two-stage least squares equation system results because of completeness, and the fact that we find some evidence of a significant reverse relationship between trading volume and bid-ask spread (see the following reported results from Table 6).

implies a restart of the index at around a level of 750. In terms of hedging the underlying index stocks with futures, the higher pre-split index level does not allow as high a degree of precision in executing hedging strategies as the lower post-split level. Moreover, after the split, the smaller contract size is likely to make the futures contract more accessible to smaller investors. One potential drawback of the split is the risk of increased trading costs, as brokerage commissions and exchange fees are quoted on a per-contract basis. However, at the OM, the per-contract exchange fees were reduced in accordance with the split, both for market makers and individual investors. Market makers might also be tempted not to fully reduce futures bid-ask spreads in accordance with the reduction in contracts size that comes with the split.

To evaluate the hedging efficiency of the futures contract before and after the split, we use a bivariate GARCH framework to jointly model stock index returns and changes in the futures basis. In this model, the optimal hedge ratio is allowed to vary over time, conditional on the available set of information, and is a function of the conditional stock index return variance, the conditional variance of the futures basis, and the conditional correlation coefficient between stock index and futures basis innovations. In addition, we obtain a time-varying measure of hedging effectiveness from the bivariate GARCH model, and we use the conditional variance of the futures basis as a measure of basis risk when employing the futures contract for hedging purposes. As such, the lower the basis risk, the better hedging tool the futures contract would be. Hence, we also explicitly investigate whether the futures split affects the basis risk, relative the overall market risk, as measured by conditional stock index variance. Apart from the bivariate time-varying GARCH setting, we also use a classical constant hedge ratio model to measure futures hedging efficiency as a benchmark in the analysis.

In a time series regression analysis with the conditional, time-varying, measures of hedging effectiveness and basis risk as dependent variables, we include a dummy explanatory variable to test whether the futures split has any effect. Our results show significantly increased futures hedging efficiency following the futures split. The results are robust against the model choice, whether we use the constant or time-varying hedge ratio model to measure hedging efficiency, and are persistent after controlling for changes in the quoted futures bid-ask spread and futures trading volume in the regression analysis. Moreover, we find a significantly lower relative basis risk after the futures split than before. The findings are consistent with the idea that the futures split has enhanced hedging effectiveness of the futures contract, and have a natural policy implication. When the futures contract size becomes “too large” due to the underlying market rallies or long term growth, the futures exchange should consider a split in order to sustain hedging efficiency.

In addition, we investigate the impact of the split on the futures bid-ask spread and trading volume. In a regression model, where the futures bid-ask spread and trading volume are endogenous dependent variables, we investigate the significance of the split-dummy variable coefficient, while controlling for volatility in futures returns. The results show no evidence that the futures split significantly affects the relative futures bid-ask spread. However, we find strong evidence that futures trading volume increase significantly as a result of the split in the futures contract. The combined consequence of these two results is that the split has enhanced the attractiveness of the futures contract in terms of investors. We find support for the idea of a broader investor base following the futures split, and find at the same time no evidence in favour of the caveat that investor transaction costs measured by futures bid-ask spreads should increase. Clearly, the results of our study are good news for investors in general and hedgers in particular at the OMX-index futures market.

Bibliography

Baillie, R., and R. Myers, 1991, Bivariate GARCH estimation of the optimal commodity futures hedge, Journal of Applied Econometrics 6, 109-124.

Bollen, N., Smith, T., and R. Whaley, 2003, Optimal contract design: for whom? Journal of Futures Markets 23, 719-750.

Bollerslev, T., 1986, Generalized Autoregressive Conditional Heteroscedasticity, Journal of Econometrics 31, 307-326.

Bollerslev, T., 1988, On the correlation structure of the generalized autoregressive conditional heteroskedastic process, Journal of Time Series Analysis 9, 121-131.

Bollerslev, T., and J. Wooldridge, 1992, Quasi-maximum likelihood estimation and inference in dynamic models with time varying covariances, Econometric Review 11, 143-172.

Brooks, C., Henry, Ó., and G. Persand, 2002, The effect of asymmetries on optimal hedge ratios, Journal of Business 75, 333-352.

Chen, Y., Duan, J., and M. Hung, 1999, Volatility and maturity effects in the NIKKEI index futures, Journal of Futures Markets 19, 895-909.

Chen, J., and P. Locke, 2004, Splitting the S&P 500 futures, Journal of Futures Markets 24, 1147-1163.

Ederington, L., 1979, The hedging performance of the new futures market, Journal of Finance 34, 157-170.

Fuller, W. (1996). Introduction to statistical time series (2^{nd} edition). New York: John Wiley & sons, Inc.

Gao, A., and G. Wang, 2005, Asymmetric volatility of basis and the theory of storage, Journal of Futures Markets 25, 399-418.

Glosten L., Jagannathan R., and D. Runkle, 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks, Journal of Finance 48, 1779-1801.

Huang, R., and H. Stoll, 1998, Is it time to split the S&P 500 futures contract? Financial Analysts Journal (February), 23-35.

Johnson, L., 1960, The theory of hedging and speculating in commodity futures, Review of Economic Studies 27, 139-151.

Karagozoglu, A., Martell, T. and G. Wang, 2003, The split of the S&P 500 futures contract: effects on liquidity and market dynamics, Review of Quantitative Finance and Accounting 21, 323-348.

Kroner, K., and J. Sultan, 1993, Time varying distribution and dynamic hedging with foreign currency futures, Journal of Financial and Quantitative Analysis 28, 535-551.

Lien, D., 2005, A note on asymmetric stochastic volatility and futures hedging, Journal of Futures Markets 25, 607-612.

MacKinnon, J., 1996, Numerical distribution functions for unit root and cointegration tests. Journal of Applied Econometrics, 11, 601-618.

Newey, W., and K. West, 1987, A simple positive semi-definite heteroskedasticity and autocorrelation consistent covariance matrix, Econometrica 55, 703-708.

Park, T., and L. Switzer, 1995, Bivariate GARCH estimation of the optimal hedge ratios for stock index futures: a note, Journal of Futures Markets 15, 61-67.

Sheskin, D., 1997, Parametric and nonparametric statistical procedures, Boca Raton: CRC Press.

Stein, J., 1961, The simultaneous determination of spot and futures prices, American Economic Review 51, 1012-1025.

Tse, Y., 2000, A test for constant correlations in a multivariate GARCH model, Journal of Econometrics 98, 107-127.

Wang, G., Yau, J. and T. Baptiste, 1997, Trading volume and transactions costs in futures markets, Journal of Futures Markets 17, 757-780.

White, H., 1980, A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity, Econometrica 48, 817-838.

Table 1: Results from the bivariate GARCH model for stock index returns and futures basis

Coefficient	*Estimate*	*t-value*	*p-value*
a_0	1.02e-3	3.913	0.0001
α_0	3.74e-6	3.229	0.0012
α_1	0.8211	44.50	0.0000
α_2	0.1677	5.922	0.0000
α_3	-0.1065	-3.280	0.0010
b_0	9.48e-3	2.874	0.0041
b_1	-0.3475	-6.312	0.0000
β_0	3.19e-7	1.998	0.0459
β_1	0.8196	18.57	0.0000
β_2	0.1239	3.262	0.0011
β_3	-0.0637	-2.409	0.0160
ρ	0.1012	3.668	0.0002
Log Likelihood	12,377.4		

Table 1 contains estimation results from the bivariate GARCH model of stock index returns and futures basis changes. The coefficients are estimated using data from the sample period October 24, 1994, through June 29, 2001, with the quasi-maximum likelihood technique, according to Bollerslev and Wooldridge (1992). The model equations are:

$$\frac{\Delta S_t}{S_{t-1}} = a_0 + \sqrt{h_t}\,\varepsilon_t \qquad h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 Q_{t-1}\varepsilon_{t-1}^2$$

$$\frac{\Delta B_t}{S_{t-1}} = b_0 m_t + b_1 \frac{B_{t-1}}{S_{t-1}} + \sqrt{q_t}\,\xi_t \qquad q_t = \beta_0 + \beta_1 q_{t-1} + \beta_2 \xi_{t-1}^2 + \beta_3 D_{t-1}\xi_{t-1}^2$$

$$Cov_{t-1}(\varepsilon_t, \xi_t) = \rho$$

where ΔS_t denotes the stock index price change from time $t-1$ to time t, ΔB_t denotes the corresponding change in the futures basis, $\varepsilon_t | \Im_{t-1} \sim N(0,1)$ is a stock index return shock at time t, $\xi_t | \Im_{t-1} \sim N(0,1)$ is a corresponding futures basis shock, $\Im_t$ denotes the information set available at time t, $N(0,1)$ is the standard normal distribution, h_t is the conditional stock index variance at time t, q_t is the conditional futures basis variance at time t, Q_t (D_t) is a dummy variable equal to one if $\varepsilon_t > 0$ ($\xi_t > 0$) and zero otherwise, m_t is the time to maturity in years of the futures contract, and ρ is the conditional correlation coefficient between the two shocks ε_t and ξ_t.

Table 2: Results from the univariate GARCH regression model for stock index returns

Coefficient	*Estimate*	*t-value*	*p-value*
$c_{0,b}$	8.73e-5	2.151	0.0315
$c_{0,a}$	1.18e-5	0.253	0.8000
$c_{1,b}$	0.9499	167.3	0.0000
$c_{1,a}$	0.9731	237.8	0.0000
γ_0	2.81e-7	4.390	0.0000
γ_1	0.9229	77.33	0.0000
γ_2	0.0626	4.680	0.0000
γ_3	-0.0373	-2.094	0.0363
θ_1	-0.5069	-20.92	0.0000
θ_2	-0.2989	-10.93	0.0000
θ_3	-0.1909	-6.453	0.0000
θ_4	-0.1457	-4.718	0.0000
θ_5	-0.0239	-0.895	0.3705
Log Likelihood	7,459.3	$\overline{R}^2 = 0.9651$	

Hypothesis tests

Null Hypothesis	*Estimate*	χ^2*-value*	*p-value*
$c_{1,b} = c_{1,a}$	-0.0232	10.89	0.0010
$c_{1,b} = 1$	-0.0501	77.85	0.0000
$c_{1,a} = 1$	-0.0269	43.27	0.0000

Table 2 contains estimation results from the univariate GARCH regression model of stock index returns. The coefficients are estimated using data from the sample period October 24, 1994, through June 29, 2001, with the quasi-maximum likelihood technique, according to Bollerslev and Wooldridge (1992). The model equations are:

$$\frac{\Delta S_t}{S_{t-1}} = c_{0,b}P_{b,t} + c_{0,a}P_{a,t} + c_{1,b}P_{b,t}\frac{\Delta F_t}{S_{t-1}} + c_{1,a}P_{a,t}\frac{\Delta F_t}{S_{t-1}} + u_t\,,\; u_t = e_t - \sum_{i=1}^{5}\theta_i u_{t-i}\,,\; e_t = \sqrt{g_t}\,\eta_t$$

$$g_t = \gamma_0 + \gamma_1 g_{t-1} + \gamma_2\eta_{t-1}^2 + \gamma_3 Z_{t-1}\eta_{t-1}^2$$

where ΔS_t denotes the stock index price change from time $t-1$ to time t, $\eta_t|\Im_{t-1} \sim N(0,1)$ is a return shock at time t, $\Im_t$ denotes the information set available at time t, $N(0,1)$ is the standard normal distribution, g_t is the conditional variance at time t, Z_t is a dummy variable equal to one if $\eta_t < 0$ and zero otherwise, and each dummy variable $P_{b,t}$ and $P_{a,t}$ equals one before and after the split respectively.

Table 3: Summary statistics

Panel A: Before the split												
Statistics	$\Delta S_t / S_t$	$\Delta F_t / S_t$	$\Delta B_t / S_t$	$\sqrt{h_t}$	$\sqrt{q_t}$	y_t	$FUTVOL_t$	$SPREAD_t$	$VOLUME_t$	m_t	x_t	φ_t
Mean	0.0011	0.0011	-0.0002	0.0112	0.0025	0.2353	0.0108	0.0011	8.3794	0.0572	0.9480	0.9262
Median	0.0012	0.0007	-0.0001	0.0103	0.0024	0.2270	0.0100	0.0009	8.3870	0.0575	0.9535	0.9321
Standard dev.	0.0111	0.0116	0.0026	0.0035	0.0005	0.0648	0.0032	0.0007	0.4621	0.0247	0.0278	0.0327
Unit root test	0.0000	0.0000	0.0000	0.0015	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001
Panel B: After the split												
Statistics	$\Delta S_t / S_t$	$\Delta F_t / S_t$	$\Delta B_t / S_t$	$\sqrt{h_t}$	$\sqrt{q_t}$	y_t	$FUTVOL_t$	$SPREAD_t$	$VOLUME_t$	m_t	x_t	φ_t
Mean	0.0004	0.0004	-8.79e-5	0.0177	0.0032	0.1932	0.0185	0.0015	8.7087	0.0574	0.9631	0.9448
Median	0.0006	0.0014	-4.66e-5	0.0169	0.0029	0.1811	0.0177	0.0011	8.7168	0.0575	0.9696	0.9522
Standard dev.	0.0189	0.0196	0.0038	0.0061	0.0009	0.0629	0.0052	0.0013	0.5572	0.0250	0.0230	0.0282
Unit root test	0.0000	0.0000	0.0000	0.0022	0.0003	0.0001	0.0000	0.0074	0.0000	0.0000	0.0001	0.0001

Table 3 contains summary statistics for stock index returns ($\Delta S_t / S_t$) futures returns ($\Delta F_t / S_t$), normalised basis changes ($\Delta B_t / S_t$), conditional stock index volatility ($\sqrt{h_t}$), conditional basis volatility ($\sqrt{q_t}$), relative conditional basis volatility ($y_t = \sqrt{q_t / h_t}$), conditional futures volatility ($FUTVOL_t$), relative futures bid-ask spread ($SPREAD_t$), natural logarithm of futures trading volume ($VOLUME_t$), futures contract maturity (m_t), conditional hedging efficiency (x_t), and conditional futures hedge ratio (φ_t). In Panel A, data are from the period between October 24, 1994, and April 27, 1998, whereas in Panel B, data are from between April 28, 1998, and June 29, 2001. The augmented Dickey-Fuller test (Fuller, 1996) is used to test the null hypothesis that each time series has a unit root. For each series, a MacKinnon (1996) one-sided *p*-value under each null hypothesis is reported.

Table 4: Independent *t*-test and Wilcoxon rank sum test before and after the split

Statistics	$\sqrt{h_t}$	$\sqrt{q_t}$	y_t	$FUTVOL_t$	$SPREAD_t$	$VOLUME_t$	x_t	φ_t
t-test	27.24 (0.0000)	20.45 (0.0000)	13.48 (0.0000)	36.67 (0.0000)	8.259 (0.0000)	13.20 (0.0000)	11.99 (0.0000)	12.41 (0.0000)
Wilcoxon rank sum test	25.13 (0.0000)	19.58 (0.0000)	14.38 (0.0000)	30.48 (0.0000)	5.602 (0.0000)	12.27 (0.0000)	14.38 (0.0000)	14.38 (0.0000)
Direction of change	increase	increase	decrease	increase	increase	increase	increase	increase

Table 4 contains a *t*-test for equality of means before and after the split, and a Wilcoxon rank sum test for equality between the corresponding medians (*p*-value in parenthesis), for the variables conditional stock index volatility ($\sqrt{h_t}$), conditional basis volatility ($\sqrt{q_t}$), relative conditional basis volatility ($y_t = \sqrt{q_t / h_t}$), conditional futures volatility ($FUTVOL_t$), relative futures bid-ask spread ($SPREAD_t$), natural logarithm of futures trading volume ($VOLUME_t$), conditional hedging efficiency (x_t), and conditional futures hedge ratio (φ_t). The Wilcoxon *p*-values are based on the asymptotic normal approximation outlined in Sheskin (1997).

Table 5: Results from the regression models for hedging efficiency and basis risk

Hedging efficiency equation (x_t)				*Basis risk equation* (y_t)			
Coefficient	*Estimate*	*t-value*	*p-value*	*Coefficient*	*Estimate*	*t-value*	*p-value*
δ_0	0.9486	178.0	0.0000	ϕ_0	0.2339	16.25	0.0000
δ_1	0.0127	3.292	0.0010	ϕ_1	-0.0370	-2.710	0.0068
δ_2	0.2162	1.254	0.2100	ϕ_2	-0.5667	-1.183	0.2368
δ_3	0.0003	0.496	0.6199	ϕ_3	-0.0003	-0.220	0.8257
δ_4	0.0084	0.495	0.6202	ϕ_4	-0.0201	-0.486	0.6270
$\theta_{x,1}$	0.8612	16.52	0.0000	$\theta_{y,1}$	0.8580	19.57	0.0000
$\theta_{x,2}$	-0.1210	-2.238	0.0254	$\theta_{y,2}$	-0.0916	-2.035	0.0420
$\theta_{x,3}$	0.0980	1.764	0.0780	$\theta_{y,3}$	0.1045	2.217	0.0268
$\overline{R}^2 = 0.7717$				$\overline{R}^2 = 0.8111$			

Table 5 contains estimation results from the regression models of hedging efficiency (x_t) and basis risk (y_t). The coefficients are estimated with non-linear least squares, where the standard errors are corrected for heteroskedasticity and autocorrelation in the residuals (10 lags) according to White (1980), and Newey and West (1987). Data are from the sample period October 24, 1994, through June 29, 2001. The model equations are:

$$x_t = \delta_0 + \delta_1 P_{a,t} + \delta_2 SPREAD_t + \delta_3 VOLUME_t + \delta_4 m_t + u_{x,t}\ ,\ u_{x,t} = e_{x,t} - \sum_{i=1}^{3} \theta_{x,i} u_{x,t-i}$$

$$y_t = \phi_0 + \phi_1 P_{a,t} + \phi_2 SPREAD_t + \phi_3 VOLUME_t + \phi_4 m_t + u_{y,t}\ ,\ u_{y,t} = e_{y,t} - \sum_{i=1}^{3} \theta_{y,i} u_{y,t-i}$$

where x_t is a conditional hedging efficiency measure on day *t*, y_t is a the conditional basis risk measure on day *t*, the dummy variable $P_{a,t}$ equals one after the split, $SPREAD_t$ is the relative futures bid-ask spread, i.e. absolute closing bid-ask spread divided by the midpoint of the bid and ask quote, of the nearby futures contract on day *t*, $VOLUME_t$ is the natural log of the number of traded nearby futures contracts on day *t*, m_t is the annualised time to maturity of the nearby futures contract, and $u_{x,t}$ ($u_{y,t}$) is a residual term in the hedging efficiency (basis risk) equation.

Table 6: Results from the regression models for futures bid-ask spread and trading volume

Bid-ask spread equation ($SPREAD_t$)				*Trading volume equation* ($VOLUME_t$)			
Coefficient	*Estimate*	*t-value*	*p-value*	*Coefficient*	*Estimate*	*t-value*	*p-value*
λ_0	-0.0008	-0.260	0.7947	ω_0	8.2269	90.08	0.0000
λ_1	-2.34e-5	-0.227	0.8206	ω_1	0.1516	2.192	0.0285
λ_2	0.0516	4.534	0.0000	ω_2	17.901	2.756	0.0059
λ_3	0.0025	2.522	0.0118	ω_3	-1.5067	-2.272	0.0232
λ_4	0.0001	0.978	0.3283	ω_4	54.804	1.791	0.0734
$\theta_{s,1}$	0.0654	2.188	0.0288	$\theta_{v,1}$	0.4000	15.40	0.0000
$\theta_{s,2}$	0.1075	4.255	0.0000	$\theta_{v,2}$	0.0792	3.322	0.0009
$\theta_{s,5}$	0.1593	4.075	0.0000	$\theta_{v,5}$	0.1023	4.153	0.0000
$\overline{R}^2 = 0.1431$				$\overline{R}^2 = 0.3220$			

Table 5 contains estimation results from the simultaneous two-equation structural model of futures bid-ask spread ($SPREAD_t$) and trading volume ($VOLUME_t$). The coefficients are estimated with non-linear two-stage least squares, where the standard errors are corrected for heteroskedasticity and autocorrelation in the residuals (10 lags) according to White (1980), and Newey and West (1987). Data are from the sample period October 24, 1994, through June 29, 2001. The model equations are:

$$SPREAD_t = \lambda_0 + \lambda_1 P_{a,t} + \lambda_2 FUTVOL_t + \lambda_3 m_t + \lambda_4 VOLUME_t + u_{s,t}\,,\ u_{s,t} = e_{s,t} - \sum_{i=1}^{5} \theta_{s,i} u_{s,t-i}$$

$$VOLUME_t = \omega_0 + \omega_1 P_{a,t} + \omega_2 FUTVOL_t + \omega_3 m_t + \omega_4 SPREAD_t + u_{v,t}\,,\ u_{v,t} = e_{v,t} - \sum_{i=1}^{5} \theta_{v,i} u_{v,t-i}$$

The two endogenous variables are the relative futures bid-ask spread $SPREAD_t$, i.e. absolute closing bid-ask spread divided by the midpoint of the bid and ask quote, of the nearby futures contract on day *t*, and the natural log of the number of traded nearby futures contracts $VOLUME_t$ on day *t*. The exogenous variables are $P_{a,t}$, which is a dummy variable that equals one after the split, the conditional futures volatility $FUTVOL_t$, and the annualised time to maturity of the nearby futures contract m_t. $u_{s,t}$ ($u_{v,t}$) is a residual term in the spread (volume) equation. The exogenous variables, together with lagged endogenous and exogenous variables are used as instruments.

Figure 1: Conditional futures hedge ratio and hedging efficiency

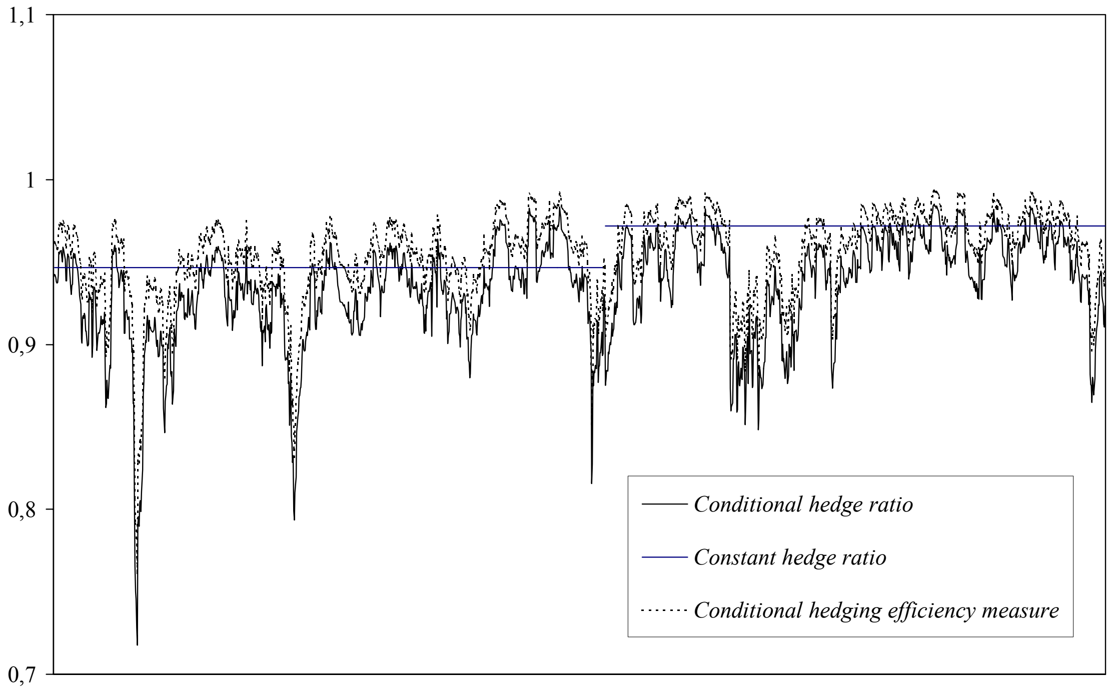

Figure 2: Conditional relative basis volatility