THE IMPACT OF CUBES ON THE MARKET QUALITY OF NASDAQ 100 INDEX FUTURES

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Abstract

Using Hasbrouck (1993) methodology and tick-by-tick intraday data, this paper investigates the market quality of Nasdaq 100 Index futures after Cubes started trading on March 10, 1999. Market quality is measured by the variance of pricing error. Pricing error is the deviation of actual transaction price from the unobserved implicit efficient price. By employing a vector autoregression model, we found a lower pricing error variance in post-Cubes period relative to that of pre-Cubes period. This finding indicates an improvement in the market quality of Nasdaq 100 Index futures.

Key words: Nasdaq, Cubes, index futures, market quality, pricing error.
JEL Classification: G14, C32.

1. Introduction

Exchange Traded Funds (ETFs) are designed to trace the performance of an index, in turn allowing the purchase and sale of an entire index in a single transaction. They also help establishing a spot position at considerably low costs. This will draw investors' attention towards index tracking stocks, and lead to a higher trading volume in both futures and ETFs. Therefore, we can expect to see a close pricing relationship between the spot and futures prices after the introduction of ETFs. While mispricing and low quality are attributed to costs associated with the spot market, trading in Cubes may result in reduced mispricing and increased market quality of Nasdaq 100 Index futures contracts.

As a new investment instrument in spot market, Cube carries the features that enable it to track the performance of the Nasdaq 100 Index quite precisely[1]. The trading of Cubes on the American Stock Exchange just like a common stock may let arbitrageurs easily establish an index arbitrage position at relatively lower costs. Thus, arbitrageurs may buy (sell) Cubes, and at the same time sell (buy) index futures to take advantage of arbitrage opportunities. As a result, index futures prices may respond more quickly to the new information and move toward the efficient price. Finally, this is expected to reduce pricing error variance and improve the market quality.

So far in the literature, ample researches have been conducted on the efficiency and the quality of futures markets. These studies generally employ cost of carry model and bid-ask spread measures (e.g., see Dwyer, Locke, and Yu, 1996; Huang and Stoll, 1997). Hasbrouck (1993), on the other hand, proposes an alternative market quality measure. By using vector autoregression (VAR) methodology, in his study, Hasbrouck (1993) computes pricing error variance to analyze the market quality for a sample of NYSE stocks. This pioneer study of Hasbrouck is widely accepted and followed in the literature to analyze market efficiency (e.g., see Tse and Erenburg, 2003; Kumar, Sarin, and Shastri, 1998).

By applying the same technique with Hasbrouck and using intraday tick-by-tick data, this paper investigates the market quality of Nasdaq 100 Index futures in 100-day periods before and after the inception of Cubes on AMEX, on March 10, 1999. We hypothesize that the introduction of Cubes enhances the market quality of Nasdaq 100 Index futures contracts.

Despite the fact that the innovators and issuers of ETFs emphasize the advantages of these instruments in terms of diversification, transaction costs and tax efficiency, there are few studies addressing the effect of ETFs on the quality of index markets particularly by utilizing high-

[1] Cubes provide several advantages in executing index arbitrage. First, instead of dealing with a portfolio of 100 securities, the index arbitrage involves only the trading of Cubes. Second, Cubes are exempt from the uptick rule. Hence by easing the cash-leg of arbitrage position, the exemption facilitates short selling.

frequency data. Unlike the other studies in the literature, to our best knowledge, this is the first study which adopts Hasbrouck's new technique for measuring market quality and applies it to Nasdaq 100 Index futures contracts by using tick-by-tick data.

In line with the hypothesis, we found a lower pricing error variance in Nasdaq 100 Index futures for the post-Cubes period compared to the pre-Cubes period. The result is an indication of improved quality of the index futures market after Cubes started trading. This improvement in the market quality is consistent with the expectation that, following a new information flow to the Nasdaq 100 Index markets, Cubes would help the adjustment process of futures and spot prices by facilitating index arbitrage.

The paper proceeds as follows: the second section provides brief discussion about studies on pricing efficiency and market quality. Along with the hypothesis, the relationship between the market quality and pricing error variance is also presented in the second section. Section three describes the data and the methodology. Empirical results are reported and discussed in the fourth section. The fifth section provides some further analyses. Finally, the paper ends with the conclusion.

2. Pricing Efficiency and Market Quality

Market Quality in Index Markets

First introduced in Canada, index tracking stocks have been a major marketing success. They gained so much popularity that, in microstructure literature, numerous researches have been conducted about the effect of index shares on market efficiency and market quality. By using daily data, Park and Switzer (1995) investigate changes in the pricing efficiency of index futures market, following the introduction of Toronto 35 Index Participation units (TIPs). They report a decrease in the mispricing of Toronto 35 Index futures contracts after TIPs started trading. This result is consistent with the expectation that TIPs ease index arbitrage activity with its lower cost.

By using intraday data, Hegde and McDermott (2004) examine the liquidity in the markets for Diamonds and Cubes, and their underlying stocks. Their findings indicate that the liquidity of component stocks shows improvements after the introduction of Diamonds and Cubes. They present evidence that both index shares have significantly lower liquidity costs over the first 50 days of trading, compared to the portfolio of their underlying stocks. They attribute this result to the lower adverse selection costs the shares incur.

Ackert and Tian (2000) and Elton, Gruber, Comer, and Li (2002), in their studies, found that SPDRs quite accurately follow the price behavior of S&P 500 index. In that sense, SPDRs may be better alternatives for trading the index portfolio. In turn, they may lower trading activity and market efficiency in other markets by diverting trading activity from those markets. However, Switzer, Varson, and Zghidi (2000) report a reduction in positive mispricing of S&P 500 Index futures market after the introduction of SPDRs.

Employing tick-by-tick data in their study, Kurov and Lasser (2002) examine the pricing relationship between Cubes and the Nasdaq 100 Index futures contracts. They found that both the size and frequency of violations in futures price boundaries appear to be reduced after Cubes started trading. They also report an increase in the speed of market response to observed violations. These imply that the introduction of Cubes has led to an improvement in the Nasdaq 100 Index futures pricing efficiency. The researchers attribute these results to the increase in the ease of establishing a spot market position after Cubes.

In a more recent study, Tse and Erenburg (2003) investigate the price discovery and market quality of Cubes. They base their analysis on the fact that the NYSE started trading Cubes in July 2001. This is a new milestone in the NYSE history since it is the first time it opens its door to trading on a security representative of stocks that are not listed in the NYSE. The authors report that the bid-ask spread is narrower on the AMEX; whereas, ECNs make the most contribution to the price discovery process. They found narrower spreads, and improvements in market quality and price discovery on all trading platforms after Cubes started trading on the NYSE.

Pricing Error Variance as a Measure of Market Quality

Hasbrouck (1993) has proposed a new method for measuring the quality of a security market. His approach decomposes transaction prices in two parts, namely random-walk and stationary components. The random walk is considered to be the unobserved implicit efficient price, and the stationary part to be the pricing error. In his approach, pricing error is regarded as the implicit cost of trading incurred by traders.

Instead of paying its fair value for a security, if traders pay the transaction price, the difference between the transaction price and the efficient price should reflect the implicit cost of trading. Therefore, the dispersion of this pricing error term is a natural measure of market quality. This new approach suggests that the pricing error variance measures how accurately the transaction price follows the efficient price. In other words, the lower the pricing error variance is, the higher the market quality will be.

In his study, Hasbrouck (1993) detects lower average standard deviation of pricing error for actively traded shares of larger firms. This finding is parallel to the assertion that active trading results in less pricing error variance, and leads to an improvement in market quality. Using Hasbrouck's (1993) method of market quality, Dunne (1996) computes the pricing error variance of the Irish Gilt market for periods before and after the introduction of market making. In his analysis, he reports that the Irish Gilt market has become rather competitive, as evidenced by a lower pricing error variance under the post-market-making trading regime.

In another study, using Hasbrouck's methodology, Kumar, Sarin, and Shastri (1998) examine whether options trading affects the market quality of the underlying security. They find a narrowing pricing error variance for the underlying security after the inception of options trading. Their result, similar to Hasbrouck's (1993) finding, shows an increase in trading volume along with an improved market quality.

Examining the impact of the FTSE 100 Index futures' transfer from outcry market to electronic market on market quality, Tse and Zabotina (2001) report that spreads are lower in the electronic market, implying higher market quality. Contradicting with this finding, the pricing error variance measured based on Hasbrouck's (1993) method is larger, implying a lower market quality. As a result of this, it may be concluded that bid-ask spread alone may not be a good measure of market quality.

Hypothesis

Cubes provide investors with a new low-cost instrument in tracking the performance of the portfolio of Nasdaq 100 stocks. Instead of using a limited number of stocks for mimicking the Nasdaq 100 index, especially traders can implement arbitrage positions by carrying out transactions on Cubes, representative of the spot market. The trading of Cubes may contribute to the quality of the Nasdaq 100 Index futures market by easing the index arbitrage transaction.

Trading Cubes in the Nasdaq 100 Index markets facilitates arbitrage in general and especially short arbitrage since arbitrageurs can take a short spot position in Cubes and simultaneously a long position in index futures. Hence prices may absorb the new information more rapidly. Fung and Draper (1999) note that the existence of constraints on short selling in a market is a cause of mispricing. Reduction in the constraints on short selling should reduce the magnitude and frequency of mispricing in the market. This will lead prices to reflect full-information values and better efficiency across markets.

Employing the market quality measurement obtained from a mix of VAR and VMA models, we tested the hypothesis whether the quality of the Nasdaq 100 Index futures market enhances after the inception of Cubes.

3. Data and Methodology

The analysis employs tick-by-tick data for Nasdaq 100 Index futures contracts traded on the Chicago Mercantile Exchange (CME). The estimation period in this study consists of two distinct time periods splitted in accordance with the inception of Cubes. The first period covers 100 trading days from October 13, 1998 through March 9, 1999, before the introduction of Cubes, and the second one covers 100 trading days from March 10 through July 30, 1999, after the introduction of Cubes.

The Nasdaq 100 Index futures data are obtained from the Institute for Financial Markets (IFM). Ticker symbol, time of the transaction, futures trade price, transaction date, expiration month of the contract are included in the data set for each transaction. Transaction prices are generally recorded whenever a change in price occurs. Four regular Nasdaq 100 Index futures contracts expire in March, June, September, and December. In each trading day, only the most active contract with the most trades is taken into account. Approximately one week before the expiration, the most active contract becomes less active, and the next nearby contract becomes the new most active contract. Considering the likelihood of containing errors, trades recorded as cancelled, corrected, or inserted, and observations reported out of time sequence are dropped from the data set. The selection of data and variables used in the study are subject to the availability of data and aim of the study.

Hasbrouck (1993) decomposes the logarithm of the observed transaction price into two components:

$$p_t = m_t + s_t, \tag{1}$$

$$m_t = m_{t-1} + w_t, \tag{2}$$

where, m_t represents unobservable implicit efficient price and it follows a random walk process. It is the expected value of a security at the end-of-trading conditional on all publicly available information at time t.

The innovation w_t as the properties: $w_t \sim \text{iid}(0, \sigma_w^2)$ and $E(w_t w_\tau) = 0$ for all $t \neq \tau$. These innovations represent information updates to the public disseminated between time t and t–1.

s_t is the pricing error which reflects the transitory difference between observed transaction price and implicit efficient price. It is also a covariance-stationary stochastic process with zero-mean and finite variance (i.e., $E(s_t) = 0$, $E(s_t^2) = \sigma_s^2$). The pricing error term is not restricted to be serially uncorrelated with itself and w_t. It is considered a proxy for market imperfections such as discreteness, inventory control, the non-information-based component of the bid-ask spread, the transient component of the price response to a block trade, etc., which are not taken into account explicitly in the model.

Even though Hasbrouck (1993) uses trading volume in his study for measuring pricing error variance, we employ return and trade indicator as variables in our analysis due to the fact that no volume information is provided for the Nasdaq 100 Index futures by the IFM. For testing the hypothesis, the pricing error variance or market quality of the Nasdaq 100 Index futures is measured by estimating a VAR model of return and trade indicator with five lags over two 100-day periods before and after the inception of Cubes as follows:

$$\Delta P_t = \theta_1 \Delta P_{t-1} + \theta_2 \Delta P_{t-2} + ... + \theta_5 \Delta P_{t-5} + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + ... + \varphi_5 x_{t-5} + \varepsilon_{1t}, \tag{3}$$

$$x_t = \delta_1 \Delta P_{t-1} + \delta_2 \Delta P_{t-2} + ... + \delta_5 \Delta P_{t-5} + \omega_1 x_{t-1} + \omega_2 x_{t-2} + ... + \omega_5 x_{t-5} + \varepsilon_{2t}, \tag{4}$$

where $\Delta P_t \equiv P_t - P_{t-1}$ is the return, and P_t is the logarithm of trade price of index futures at time t. x_t is the trade indicator variable at time t. The value of +1 and –1 indicates buy and sell orders respectively. The error terms possess the following features: $Var(\varepsilon_{1t}) = \sigma_1^2$, $Var(\varepsilon_{2t}) = \sigma_2^2$, $Cov(\varepsilon_{1t}, \varepsilon_{2t}) = \sigma_{12}$, $Cov(\varepsilon_{1t}, \varepsilon_{1j}) = 0$, and $Cov(\varepsilon_{2t}, \varepsilon_{2j}) = 0$ for all $t \neq j$. The variance-covariance matrix also comes from the VAR model.

Since the IFM data set does not provide information on bid and ask quotes, in order to identify buy and sell orders we applied Lee and Ready's (1991) tick test to trade prices. The test classifies a trade as a buy (sell) if it appears on an uptick (a downtick) or a zero uptick (zero downtick).

Following Hasbrouck (1993), overnight returns are dropped and lagged values of the trades and returns are set to zero prior to each day's first transaction. Similar to Hasbrouck (1991), we assume that the VAR model is invertible and the return and trade indicator can be represented by a vector of moving average (VMA) process as below:

$$\Delta P_t = \theta_0^* \varepsilon_{1t} + \theta_1^* \varepsilon_{1t-1} + \ldots + \theta_{10}^* \varepsilon_{1t-10} + \varphi_0^* \varepsilon_{2t} + \varphi_1^* \varepsilon_{2t-1} + \ldots + \varphi_{10}^* \varepsilon_{2t-10}, \tag{5}$$

$$x_t = \delta_0^* \varepsilon_{1t} + \delta_1^* \varepsilon_{1t-1} + \ldots + \delta_{10}^* \varepsilon_{1t-10} + \omega_0^* \varepsilon_{2t} + \omega_1^* \varepsilon_{2t-1} + \ldots + \omega_{10}^* \varepsilon_{2t-10}. \tag{6}$$

Parallel to Hasbrouck (1993), the VMA coefficients are estimated by stepping the system forward in response to a unit shock. The VMA model is truncated at ten lags. In order to compute pricing error variance, we use the information coming from coefficient estimates of VMA model and the estimated variance-covariance matrix of the VAR model as follows;

$$\sigma_s^2 = \sum_{j=0}^{9} \left(\eta_j^2 \sigma_1^2 + 2\eta_j \gamma_j \sigma_{12} + \gamma_j^2 \sigma_2^2 \right), \tag{7}$$

where $\eta_j = -\sum_{k=j+1}^{10} \theta_k^*$ and $\gamma_j = -\sum_{k=j+1}^{10} \varphi_k^*$.

4. Results

First, using the information from VAR model in equations (3) and (4), and VMA model in equations (5) and (6), summary measures of the pricing error variance (or market quality) are estimated as in equation (7) for the Nasdaq 100 Index futures over each 100-day period before and after the inception of Cubes[1]. There are 60,893 trade prices in the pre-Cubes period while there are 92,342 trade prices in the post-Cubes period[2].

Estimation results are reported in Table 1. Part A in the table contains estimation results of pricing error variances for pre and post-Cubes periods over 100 trading days. As Part A reveals, we identified a lower pricing error variance of 0.0078 in the post-Cubes period compared to that of 0.7878 in the pre-Cubes period. Hence our findings show that market quality of Nasdaq 100 Index futures improves after Cubes started trading, implying that index futures prices track the efficient price more closely[3]. A possible explanation for such a drastic difference in pricing error variances between the two periods might be the ''learning by trading'' process. That is, as traders are accustomed to the features of Cubes and learn how to use them properly, they may be able to make better estimates of the fair value. Indeed, this process may take some time. In that sense, as the number of trading days extends, it would be normal to observe an increase in the magnitude of pricing error variance differences in the both periods[4].

In addition to computing pricing error variances for 100-day periods, we also estimated pricing error standard deviations for each day over the two periods. These estimates are used to

[1] In an attempt to verify that the results are not affected by the sample size, the analysis is also performed for each 50 and 75-day periods both before and after Cubes. Pricing error variances of 0.2273 and 0.0529 are obtained for 50-day pre and post-Cubes periods, respectively. Pricing error variances of 0.4288 and 0.0085 are calculated for 75-day pre and post-Cubes periods, respectively. These findings are consistent with those for 100-day periods, supporting the view that the quality of Nasdaq 100 Index futures improves following the introduction of Cubes.

[2] The difference in the number of trades between the two periods becomes more apparent as moved forward in time (e.g., 215,607 trades in post-period versus 114,929 trades in pre-period for 200 trading days). This may support the view that Cubes facilitate index arbitrage, which is also consistent with the findings of Hegde and McDermott (2004), and Tse and Erenburg (2003).

[3] See Kayali (2002) and Chu and Kayali (2006) for similar results.

[4] We computed the ratio of pricing error standard deviations between pre and post-Cubes period $\left(i.e., \frac{\sigma_s^{pre}}{\sigma_s^{post}} \right)$ for 50, 75 and 100 trading days. The estimation results are 2.1, 7.2 and 10.1, respectively. These findings, to some extent, support our ''learning by trading'' argument.

test the null hypothesis that the mean standard deviations in the two periods are not different from each other. The results are reported in Part B of the table. The mean standard deviation of pricing error is 0.0195 and 0.0129 in the pre-and post-Cubes periods, respectively. The comparison of the mean standard deviations using t-test yields a t-statistic of 5.69. This indicates that the mean standard deviations are significantly different from each other at the 1 percent level.

A non-parametric Mann-Whitney U test, which produced a z-statistic of -5.93, is performed to ensure that the findings are not sensitive to the assumption of a specific distribution. The results support the hypothesis that pricing error variance is lower in the post-Cubes period than in the pre-Cubes period. This verifies the improvement in the market quality of Nasdaq 100 Index futures after Cubes started trading.

5. Further Analysis

We also examined whether our hypothesis is sensitive to structural change and seasonality. The analysis is based on the assumption that the efficient price behaves similarly in the two periods. Thus, to check the validity of this assumption, we carried out a test on if any structural change exists in daily futures prices from one period to the other. In this case, our null hypothesis is that the mean daily price changes are not different in two periods. The results are presented in Part C of the table. The test produces a t-statistic of 1.048 with a p-value of 0.296. The test statistic fails to reject the null hypothesis. This implies that there is no structural change in daily futures prices. Therefore, any improvement in the market quality after Cubes may be credited to development in the microstructure aspects of the Nasdaq 100 Index futures, such as index arbitrage activities, the ease of short sales, etc.

Another analysis is conducted to test whether any effect of seasonality and sensitivity to sample period selection exists. This is carried out since the sample periods used in our first analysis do not cover the same part of the year. Therefore, the same pricing error variance analysis is applied to two 50-day periods overlapping the same times of the years. These two samples cover the dates of October 20 through December 31, 1998 for the pre-Cubes, and October 21 through December 31, 1999 for the post-Cubes periods.

The results on this analysis are reported in Part D of the table. A lower variance of 0.0503 is computed for post-Cubes period compared to that of 0.6136 for pre-Cubes period. This finding is also consistent with the previous one that the market quality improves following the inception of Cubes. Thus, it can be concluded that the results are not sensitive to seasonality and the sample periods selected.

Table 1

Estimation Results

Part A:	Pre-Cubes		Post-Cubes
Time period	98/10/13-99/03/09		99/03/10-99/07/30
Pricing error variance (σ_s^2)	0.7878		0.0078
Pricing error standard deviation (σ_s)	0.8876		0.0883
Number of trade prices	60,893		92,342
Part B:			
H_0: $\sigma_{mean}^{pre} = \sigma_{mean}^{post}$			
H_1: $\sigma_{mean}^{pre} \neq \sigma_{mean}^{post}$			
Mean daily pricing error std. dev. (σ_s)	0.0195		0.0129
Number of trading days	100		100
Average number of trade prices per day	609		923
t-test		t = 5.69*	
Mann-Whitney U test		z = -5.93*	

Table 1 (continuous)

Part C:	Pre-Cubes		Post-Cubes
H$_0$: $\mu_{pre} = \mu_{post}$			
H$_1$: $\mu_{pre} \neq \mu_{post}$			
Mean daily price change	0.00507		0.00165
t-statistic		t = 1.048**	
p-value		p = 0.296**	
Part D:			
Time period	98/10/20-98/12/31		99/10/21-99/12/31
Pricing error variance (σ_s^2)	0.6136		0.0503
Number of trading days	50		50

* Statistically significant at the 1 percent level.
** Statistically not significant at conventional levels.

6. Conclusion

By using Hasbrouck (1993) methodology and tick-by-tick data, this study investigates the effect of Cubes on the market quality of the Nasdaq 100 Index futures market for 100-day periods before and after the inception of Cubes. We identified a lower pricing error variance (or better market quality) for index futures market in post-Cubes period compared to pre-Cubes period.

In parallel to explanation in the literature (e.g., see Fung and Draper, 1999; Fung, Jiang, and Cheng, 2001) that securities prices should follow the efficient price more closely as restrictions to short selling of those securities are lifted, the inception of Cubes may ease trading in the spot market and allow seizing arbitrage opportunities. That is, arbitrageurs would be able to take a spot position by purchasing or short selling Cubes. Hence, it can be expected that variation in pricing errors would be lower and in turn the quality of index futures market would improve after Cubes started trading. Our findings are consistent with this expectation, and provide supporting empirical evidence.

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