

Empirical Analysis of the Dow Jones Futures Pit Since the Introduction of Side by Side Computer Trading

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Abstract

The introduction of side-by-side computer trading of Dow Jones Industrial futures at the Chicago Board of Trade began in September 1999. This study examines the change in efficiency of the open-outcry market of Dow Jones futures since this introduction. It examines over five hundred thousand transactions, which took place in the Dow Jones pit at the Chicago Board of Trade, and runs a number of tests and regressions on these data. The results conclude that the bid-ask price bounce is the best estimator for the spread, that a full day is the most desirable time period of analysis, and that the open-outcry market is significantly more efficient since the introduction of side-by-side computer trading.

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I. Introduction

Technological advances have changed the face of financial markets over the past twenty years. Developments in computer technology and computer programming have changed the way financial assets are traded. Computer trading markets may soon eliminate the traditional open-outcry trading markets¹. This study is going to focus on the development of computer trading of Dow Jones Industrials futures at the Chicago Board of Trade (CBOT) and its effect on the open-outcry market. In late 1999 computer trading of futures and options at the CBOT began to take place along side open-outcry trading. This means that computer trading takes place during the same trading hours as floor trading. Computer trading for most commodities was not originally done side-by-side but rather computer trading took place during specific hours when the trading pit was closed. This was the case for all the commodities traded at the CBOT before September 1999. All of the other commodities at the CBOT have also gone to side-by-side trading in an attempt, some may say, to be more efficient.

The Dow Jones Industrial Average is a price weighted portfolio of the thirty largest and best known U.S. stocks. The weighted average is calculated using the sum of the prices of the thirty stocks divided by the Dow Divisor², which is calculated by the CBOT and is available on their website (www.CBOT.com). The Dow Jones futures pit was created in 1998 and allowed investors/traders to speculate and hedge an extremely diversified index of powerful U.S. stocks.

¹ Market where the method of communicating trades involves shouting and hand signals.

² A scalar used to give different weights to each individual stock in the Dow Jones Industrials.

A futures contract is a standardized contract to buy or sell a certain quantity of a commodity at a set price at a set date in the future (Hull 2002). This contract gives the trader the right or obligation to buy or sell that amount of the commodity at the certain price on the expiration date of the contract. While this contract may seem complicated, in the Dow Jones Futures pit only a very small percentage of the contracts are actually held until expiration.

Futures have traditionally been traded in an open out-cry market where traders yell and use hand signals to buy and sell futures. In these pits there are two types of traders: brokers who are buying and selling for themselves and/or for customers; and locals who are only buying and selling for themselves. In order to buy or sell a future a non-member must go through a broker who in turn must trade with either another broker or a local. As you can imagine the customer might not get the best price because of potential conflicts of interest among participants.

Toward the end of 1999 the CBOT began to move towards the establishment of side by side electronic trading of Dow Jones futures. But instead of providing the same commodity that was traded in the pit, it developed a miniature contract that was half the size of the contract traded in the pit. This would become the “Dow mini” contract which would strictly be traded on the computer. The Dow mini provided an alternative to the Dow futures pit and also allowed smaller investors an opportunity to participate in the market because the contracts were half the size. Because of the half sized contract most large orders still had to go through the pits. Recently the CBOT has created a new electronic market but its contract is 2.5 times larger than the future contract traded in the pit which may spell the end of the Dow futures pit.

An abundance of literature has emerged about whether computer trading is more efficient than the traditional open outcry market. The literature is mostly mixed because of the conflicting definitions of market efficiency and the bid-ask spread. More recent studies seem to support the conclusion that computer trading has resulted in more efficient markets. This recent shift may be because the initial transaction costs associated with the move to computer trading have declined leading to more efficient markets. This study poses a different question. Is the market more efficient because of computer trading.

The analysis will use some of the methods developed in the Cheng, Fung, and Tse (2005) study of the Hang Seng Index and apply them to the Dow Jones futures market. Because the CBOT does not quote the bid-ask spread a number of different estimation methods are examined. Market efficiency in this study will measure efficiency as defined by Eugene Fama (1970). The “Efficient Market Hypothesis” assumes that all information in the market is accounted for in the price of the commodity being bought or sold. This definition allows for efficiency to be explained by the bid-ask spread. As the bid-ask spread decreases, more information is being internalized by the market and therefore the market is more efficient and moving toward an equilibrium.

Section II summarizes the literature and explains the estimation of the bid-ask spread from time and sales data. **Section III** describes the data used for this research. It also provides an overview of the empirical methods and a report of the empirical results. **Section IV** summarizes the results, discusses the implications of the research and points the way to possible further study.

II. Literature Review

Cheng, Fung and Tse (2005) conducted an empirical analysis of the Hang Seng Index³ futures. Using transaction, volatility, and daily high and low data for futures, calls and puts, they were able to formulate an equation for the bid-ask spread. Because the Hang Seng records intraday bid-ask spread quotes they used these data in their analysis. Transaction data are records of trades that take place throughout the day. Volatility measures the risk associated with the market, and Cheng *et al* (2005) use daily highs and lows to calculate volatility. Finally the bid-ask spread is the difference between the lowest price at which someone is willing to sell a commodity and the highest price someone is willing to pay for the same commodity.

Using a binary variable for before and after computer trading, Cheng *et al* (2005) were able to measure the impact of the switch. They found that the coefficient of the variable used to control for the switch to computer trading was negative and significant. This indicated that the bid-ask spread decreased after the switch to computer trading for futures and options. They also used compound regressors between the binary variable and volatility and the binary variable and time to maturity after the switch. They found that volatility had a bigger impact after the switch to computer trading. Time to maturity had no significant impact on the bid-ask spread either before or after the switch to computer trading.

³ A capitalization-weighted stock market index of the Hong Kong Stock Exchange.

The authors also examined the average spread observed in the futures market and found that the spread was drastically lowered after the introduction of computer trading; the bid-ask spread for futures decreased by 20.72%. They concluded that computer trading has made the Hang Seng Index futures market more efficient based on the decrease in the bid-ask spread following its introduction. These results imply that computer trading is more efficient than pit trading when the shift goes from completely floor trading to completely computer trading, excluding a couple months in which the market internalizes the new system.

While Cheng *et al* (2005) do a very good job of empirically analyzing the shift to computer trading, they fail to offer any reasons as to why computer trading is more efficient. Frino, Harris, and McNish (2004) examine an important part of pit trading which is the monopoly power of the pit trader. They found that, because pits have a limited number of individuals participating in trading, each individual trader has some monopoly power. Computer trading eliminates a portion of the monopoly power of the pit traders making the market more efficient.

On the other hand, one reason why computer trading may not be as efficient as the traditional open-outcry market is that it has emerged recently and has been dubbed the "fat finger" problem. This happens when mistakes are made typing orders into the computer. These errors can be outrageous as seen on the Tokyo Stock Exchange on December 8, 2005 when an employee of Mizuho Securities placed an order to sell 610,000 shares at 1 yen instead of selling 1 share at 610,000 yen. The error cost the brokerage firm almost 40 billion yen. Errors like this one are few and far between but they can have huge impacts on a market (Greimel 2005).

Tse (1999) provided another empirical analysis of a futures market, FT-SE 100⁴ index futures, which made a clear distinction between the bid-ask spread of a futures market and the bid-ask spread of a stock market. Tse found that bid-ask spread estimators of stock prices are not efficient estimators for a futures market. He used Roll's estimator (1984) which defined the effective bid-ask spread for stocks as:

$$S_A = 2 \sqrt{-\text{cov}(\Delta P_t^o, \Delta P_{t-1}^o)} ;$$

where S_A is the effective bid-ask spread, P_t^o is the stock price at time t and P_{t-1}^o is the stock price at $t-1$. While this estimator is simple in theory it is troublesome in practice, especially in a futures market. Smith and Whaley (1994) show that the covariance of the S&P 500⁵ futures market produced a positive value over a significant number of the days examined implying a growing spread. Because of this practical problem Roll's estimator did not provide a usable measure of the spread because the estimation would produce an imaginary number.

Smith and Whaley (1994) discuss a number of different spread estimators from time and sales data⁶. The authors develop a method of moments estimator, and conclude that it is the best way to estimate the bid-ask spread. They define the effective bid-ask spread as the cost of immediate exchange of a commodity, and they conclude that both Roll's estimator (1984) and the bid-ask price bounce, which is the change in price between intraday quotes, are both biased estimators. They examine each estimator and find that the bid-ask price bounce is somewhat upwardly bias because it captures the bid-ask spread and also the variance of true price changes, while Roll's estimator when

⁴ A shared index of the 100 most highly capitalized stocks on the London Stock Exchange.

⁵ Index containing 500, mostly American, high-cap companies.

⁶ Data that records the time and the price at which a trade took place.

calculated for futures often produces a positive covariance leading to a failure in the estimation.

Holder and Sinha (2004) examine bid ask spread determinants at the CBOT to see how changes in the pit affect the bid-ask spread. They introduced numerous variables associated with pit trading that could have an effect on the spread. Because the spread is not quoted at the CBOT, they looked at a number of different estimators settling on the mean absolute price deviation.

The mean absolute deviation (MAD), and the bid-ask price bounce (BAB) are both fairly simple to calculate and are intuitively appealing estimators of the bid-ask spread. Additionally most of the other estimators of the bid-ask spread are based on one or both of these estimators (Holder and Sinha 2004). Their acceptance in the literature, their ease of calculation and their intuitive appeal make MAD and BAB the most feasible measures of the spread.

III. Data Overview

Collecting the data was one of the most difficult parts of the project. While transaction data are available, the major challenge is that the CBOT does not quote the bid-ask spread. Another challenge was how to structure the data that are available. The data are broken down into three different subsets. The first is March and April 1999 for the open auction market of the Dow Jones futures; this is the data before computer trading. This set is composed of time and sales data for the trading day 7:20 a.m. to around 3:30 p.m. depending on the length of the modified session, which is an extra session held after the final bell to allow traders to either get out or into a position before

pit trading is closed. Time and sales data are unusual because the time between each sale can vary making it difficult to look at the change in price over a specific time period. The data look at the price for a specific transaction at a specific point in time.

A second data set is for March and April 2001 which is just after the shift to side-by-side computer trading. The third data set is the most recent, March and April 2006, in which both methods of trading occurred. The 1999 data represents the time before the introduction of computer trading. The 2001 data looks at the period right after the shift to see if it seemed as though it took time for the market to internalize the shift. The 2006 data gives insight into how the market is currently functioning. To control for seasonal market factors the same month, April, and the same days are used for each year.

Although data are available for both March and April, focusing on April allowed for more calculations to be made and tests to be run. For consistency the data are all front month⁷ traded quotes.

Methodology

The first calculations and tests attempt to give an overall look into the efficiency of the market by examining a simple first order regression of price on lagged price which is the previously traded price. Based on the efficient market hypothesis this is a common way of measuring market efficiency. Using these two variables a simple regression was run for each day with P_t equal to the price at transaction t , and P_{t-1} equal to the price at transaction $t-1$ ⁸.

$$P_t = \alpha_0 + \alpha_1 P_{t-1} \quad (1)$$

⁷ Month determined by the pit committee, usually the month closest to expiration.

⁸ The time between transactions may vary, but is usually less than a minute.

In general a more efficient market will have a less significant α_1 which means lag-price has less effect on the current price leading to a more efficient market as described by Fama (1970). Running this regression using every trading day of April for 1999, 2001 and 2006 produced coefficients for each year. In order to test these calculations the null hypothesis $H_0: \alpha_{1B} - \alpha_{1A} \leq 0$ is used, where α_{1B} are the coefficients from the regressions before the switch to side-by-side computer trading and α_{1A} are the coefficients after the switch. The alternative is $H_1: \alpha_{1B} - \alpha_{1A} > 0$. The p-values ranged from .0001 to .7345. The evidence was not conclusive that there were efficiency gains assuming a day as the unit of observation.

I used a number of different methods in order to estimate the bid-ask spread before and after computer trading. The first estimator of the spread is the mean absolute price deviation.

$$\mathbf{MAD}_0 = \text{absolute value } (p_0 - \mu_p); \quad (2)$$

where p_0 is the price at transaction 0 and μ_p is the mean of the price throughout the corresponding period. If one assumes, as is usually the case, that a decrease in MAD implies movement to equilibrium then the market seems to reach an equilibrium a number of times throughout the day.

Chart 1:

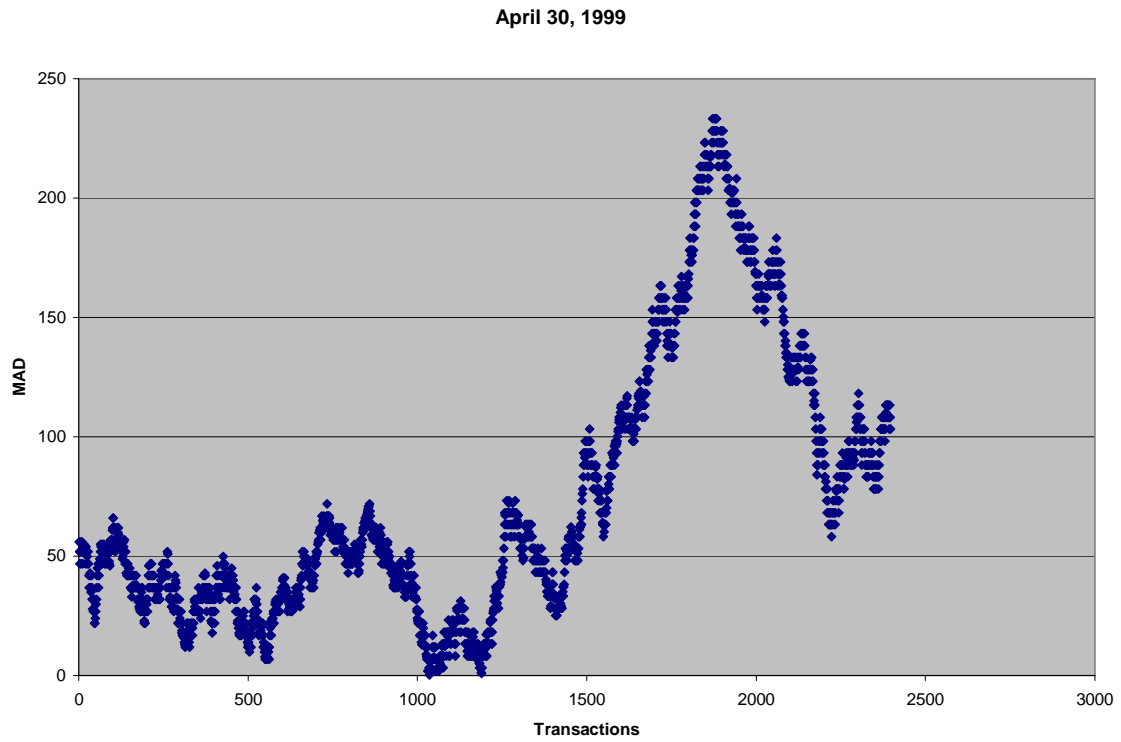


Chart 2:

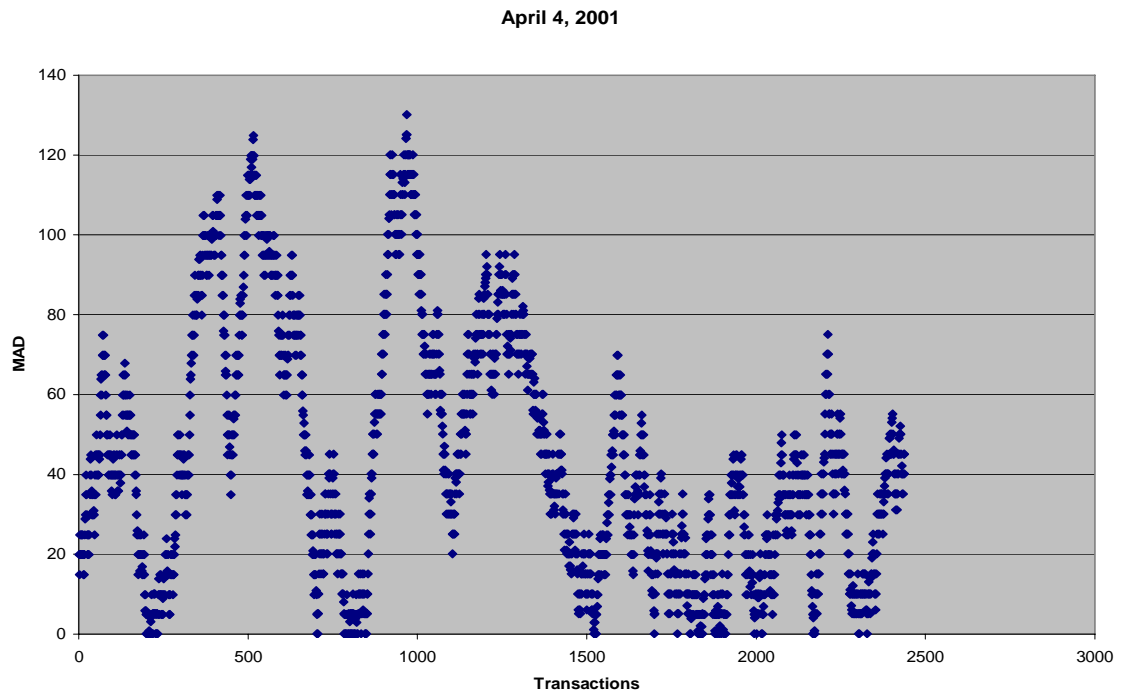
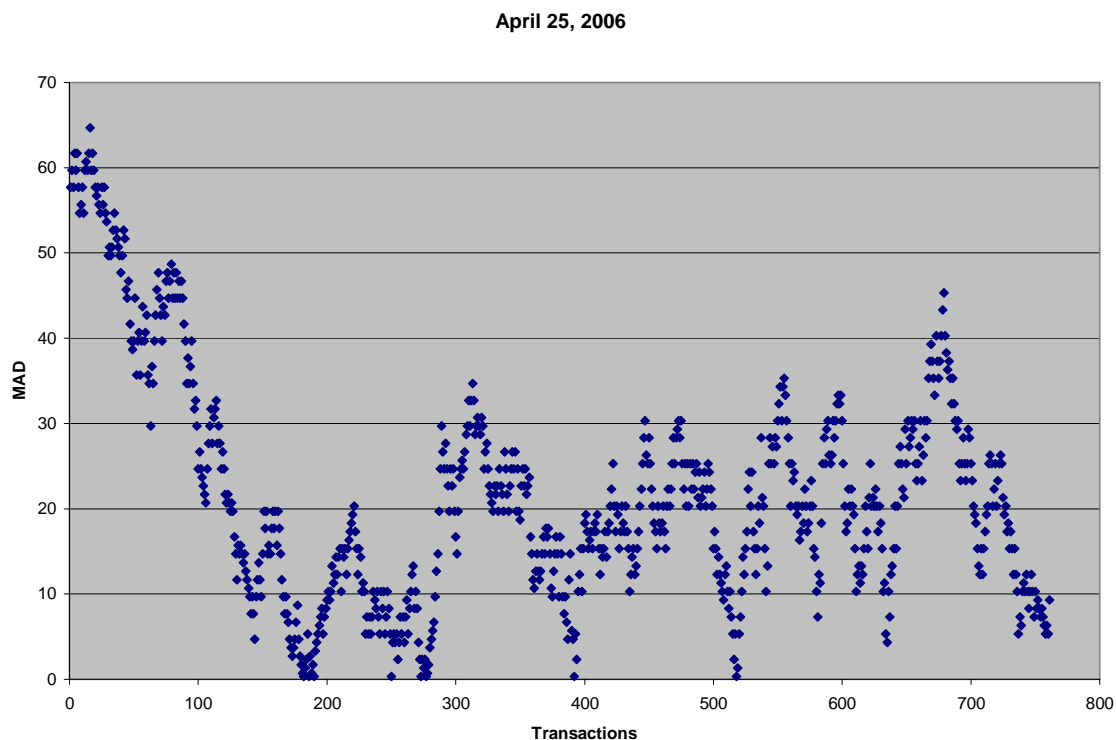


Chart 3:



The above charts are representative of how the average day looks. They pose a number of questions as to how the data should be divided, and if there are significant differences among 1999, 2001 and 2006. It seems logical to begin the examination of the market by looking at intraday data and then expanding to a comparison among days.

Calculating the average MAD over two hour intervals of trading for April 30, 1999, April 4, 2001, and April 25, 2006 and assuming independence, a hypothesis test was performed to examine the MAD before (MAD_B) and the MAD after (MAD_A) the switch with $H_0: MAD_B - MAD_A = 0$ against the one tailed alternative $MAD_B - MAD_A > 0$ with an $\alpha = .10$. The test is run to see if there was a significant difference between MAD_B and MAD_A . Between 1999 and 2001, 37.5% of the time H_0 was rejected and between

1999 and 2006, 62.5% of the time H_0 was rejected. These hypothesis tests do not show a consistent positive and significant difference between the MADs before and after.

Some insight into these mixed results may be gotten by examining the above charts. Intraday data may not capture the entire movement to equilibrium or may include multiple equilibria. During the day the market is taking on information and reaches equilibria after different numbers of transactions (periods of time) for each day. Tse (1999) found that the bid ask spread in futures markets tends to be stable over a whole day, but during the day they can vary sharply, especially during the open and close of the market. So looking at intra-day data and trying to compare the MADs before and after the switch is problematic because the market's spread may behave differently over the course of the day.

The second estimator of the bid-ask spread is a little simpler and possibly a better estimate for the Dow Jones futures market. The Bid-Ask Price Bounce (BAB) or price bounce is described as:

$$\text{Bid-Ask Price Bounce (BAB)} = |p_0 - p_1|; \quad (3)$$

where p_0 is the price at transaction 0 and p_1 is the price at transaction 1. This is the absolute price change between transactions. The smaller the change in price per transaction the more fluid the market therefore more efficient. Fluidity in a futures market can be examined through the volume of trades but also through the bid-ask spread. If the bid-ask bounce is smaller it lowers the initial cost of entering the market therefore making the market more fluid. A number of tests will be run using the bid-ask bounce or the average of the bid-ask bounce as the spread.

Chart 4:

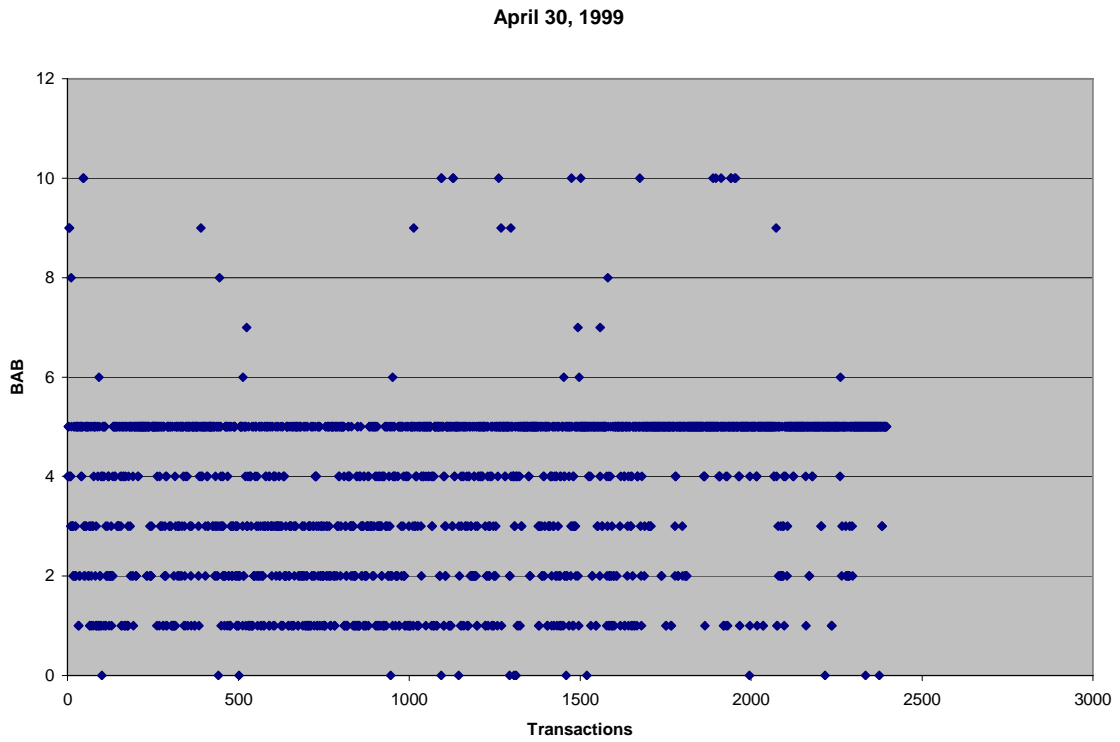


Chart 5:

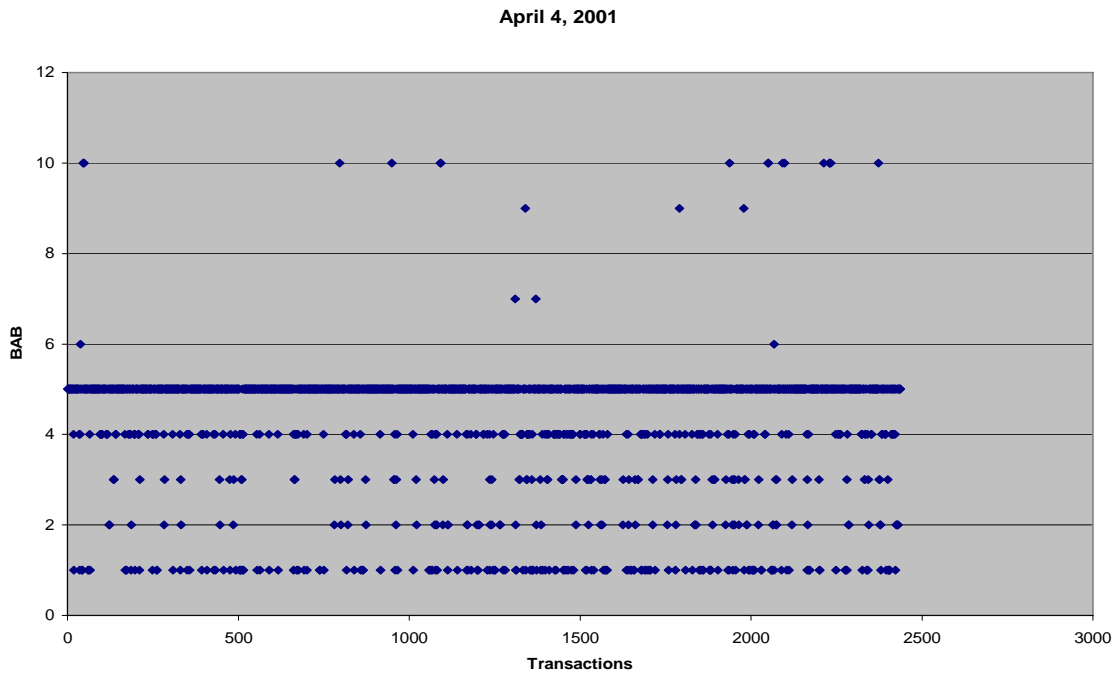
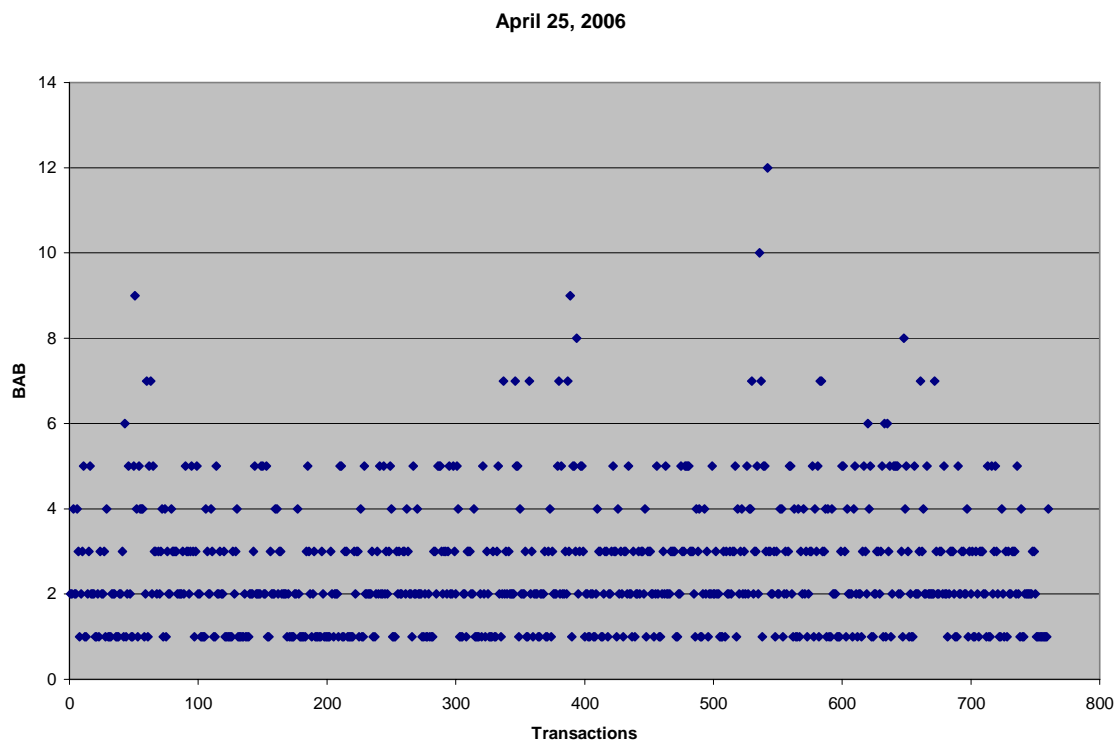


Chart 6:



Charts 4, 5 and 6 examine BAB for the same periods as were used for MAD. The average BAB decreases from 1999 and 2001 to 2006. In 1999 and in 2001 the BAB seems to cluster at around five and in 2006 the BAB seems to cluster more at two showing a decrease in the estimated bid-ask spread.

As was done for the MAD calculations above, the averages of the BAB over different time periods were examined and tested against the hypothesis $H_0: BAB_B - BAB_A = 0$ against the one tailed alternative $BAB_B - BAB_A > 0$ with an $\alpha = .10$. Between 1999 and 2001 H_0 was rejected only 29.6% of the time, but between 1999 and 2006 H_0 was rejected 84.4% of the time. The hypothesis tests do not show a consistent decrease in the spread between 1999 and 2001, but for 1999 to 2006 the tests do point to a decrease in the spread.

Two other tests were run to examine market efficiency using the variance of the spread estimators before and after. Letting σ_B^2 be the population variance before and σ_A^2 be the population variance after, the null hypothesis $\sigma_B^2 = \sigma_A^2$ with a two tailed alternative was tested. The null hypothesis is tested using an F-test

$$F = \frac{s_B^2 / \sigma_B^2}{s_A^2 / \sigma_A^2}; \quad (4)$$

Where s_B^2 and s_A^2 are the sample variances and σ_B^2 is assumed equal to σ_A^2 . The results of this test show that for MAD there does not seem to be any significant difference between the variances before and after.

Using a similar test but with the bid-ask price bounce as the spread estimator instead of the MAD similar results were found. The sample variances of the BAB estimator also led to the rejection of the above null hypothesis for certain days and the failure to reject for other days. The test failed to show a clear cut difference between the variance of BAB before and after computer trading was introduced.

While it is beneficial to examine intra-day data, problems arise in identifying the appropriate time interval to analyze. One approach is to assume the entire day as the basis of analysis. Using the tests laid out above daily average data are examined by taking the average of the MAD and BAB over each day. The tests results differed from the examination of intraday data. The hypothesis tests for MAD between April 1999 and 2001 did not indicate significant differences, but the tests run between April 1999 and April 2006 were consistently positive and significant. The hypothesis tests for the BAB did not indicate a significant decrease between April 1999 and 2001, but for April 1999 and 2006 the results are consistently positive and significant. The results for 1999 to 2006

point towards a significant decrease in the estimated bid-ask spread after the switch to side-by-side computer trading.

The results for the tests of variances using the F test were similar to the intraday data showing that the null hypothesis $\sigma_B^2 = \sigma_A^2$ can not be consistently rejected. Using all the days for March and April 1999, 2001, and 2006 there were forty-four days before the switch to side-by-side computer trading and eighty-four days after the switch for a total of one hundred and twenty-eight days. Using only March and April for 1999 and 2006 there were forty-four days before the switch and forty-two days after the switch for a total of eighty-six days.

Table 1:

| Date | BAB | MAD | % change BAB | % change MAD |
|------------|----------|----------|----------------------|----------------------|
| 1999 April | 3.632109 | 69.30395 | -32.82% 1999-2006 | -68.60% 1999-2006 |
| 2001 April | 4.374614 | 45.15544 | 20.44% 1999-2001 | -34.84% 1999-2001 |
| 2006 April | 2.439882 | 21.76283 | -44.23% 2001-2006 | -51.80% 2001-2006 |

The MAD did not show any significant change in the hypothesis tests that were run between 1999 and 2001, but looking at the average MADs did show a significant decrease between the years 1999 to 2006 as shown in **Table 1**. Also the BAB produced similar results for the period from 1999 to 2006 but showed an increase between 1999 and 2001. The reason this may have occurred is discussed in Cheng *et al* (2005). The market needs time to internalize the shift to computer trading. The results from **Table 1**

and the hypothesis tests point to a less efficient market immediately following the switch. By 2006 the market would have internalized the new system creating greater efficiency.

Because daily data provided the most consistent results and the most manageable data set, it was used in the regression analysis. Cheng, Fung and Tse (2005) estimate the spread with the following equation:

$$\mathbf{Spread} = \alpha_0 + \alpha_1 TTM + \alpha_2 Volatility + \alpha_3 D + \alpha_4 D \times TTM + \alpha_5 D \times Volatility + \varepsilon_t ; (5)$$

where **Spread** is the daily average of the absolute bid-ask price bounce; *TTM* denotes time to maturity of the contract for each day (the number of days until the expiration date on the future, or the day the future contract must be executed); *Volatility* represents the log difference between day high and day low of spot month future contracts; and *D* is a binary variable that separates the period before and after the change where *D*=0 before the change and *D*=1 after the change.

Estimating α_3 is an especially important part of the discussion because it gives an estimate of the effect of the introduction of computer trading on the efficiency of the market. If computer trading has made the open-outcry market more efficient, α_3 will be significantly negative. The other coefficients associated with *D* will give insight into how *TTM* and *Volatility* affect the bid ask spread before and after computer trading. *TTM* or time to maturity should have an insignificant effect, because most traders in the Dow Jones pit are not holding open positions until expiration. *Volatility* should have a significant positive impact on the bid-ask spread and α_2 and α_5 will show this impact.

Table 2
The Determinants of Spread

| | | Period 1999, 2001 and 2006 | | | | | | | R^2 | Adj R^2 |
|--------------------------------|-----------|-----------------------------------|------------|------------|------------|------------|------------|-------|-------|-----------|
| | N | α_0 | α_1 | α_2 | α_3 | α_4 | α_5 | | | |
| Futures (BAB) | 128 | 3.443 | -0.003 | 18.493 | -1.219 | -0.001 | 71.480 | .6368 | .6219 | |
| Spread | (t value) | (11.291)* | (-.671) | (1.624) | (-3.544)* | (-.219) | (5.450)* | | | |
| * significant at a 0.05% level | | | | | | | | | | |
| | | Period 1999 and 2006 | | | | | | | R^2 | Adj R^2 |
| | N | α_0 | α_1 | α_2 | α_3 | α_4 | α_5 | | | |
| Futures (BAB) | 86 | 3.443 | -0.003 | 18.493 | -1.112 | .002 | -1.607 | .8889 | .8820 | |
| Spread | (t value) | (27.269)* | (-1.621) | (3.922)* | (-6.031)* | (.782) | (-1.28) | | | |
| * significant at a 0.05% level | | | | | | | | | | |

Period 1999, 2001 and 2006 shows the results of the regression including all the daily data from March and April 1999, 2001 and 2006. Period 1999 and 2006 shows all the daily data for only March and April 1999 and 2006.

The regression gives more insight into how the open out-cry market has changed since the introduction of side-by-side computer trading. The significantly negative coefficient on the binary variable in both regressions shows that there has been a decrease in the daily average of the estimated bid-ask spread since the introduction of computer trading. Other significant results are the change in the coefficients on volatility alone and the binary variable and volatility when the 2001 data is excluded. Volatility alone has a significant positive impact on the spread when 2001 data is excluded but when 2001 data is included Volatility alone is not significant, but rather the binary variable and volatility is significant. The significance of these variables in the separate regressions confirms the assumption that volatility has a significant positive impact on the spread.

Finally an F-test was run on the regressions to examine the significance of the binary variable using the null hypothesis $H_0: \alpha_3=\alpha_4=\alpha_5=0$ against the two tailed alternative $H_1: \alpha_3, \alpha_4$ and/or $\alpha_5 \neq 0$. For both of the regressions the null hypothesis was

rejected, with the F stat for the first regression equal to 11.64 and the F stat for the second regression equal to 111.42, concluding that the binary variable is significant.

IV. Summary and Conclusions

The overall results support my prior expectations, but the efficiency of the market as a whole is difficult to examine because the market is constantly taking on new information and moving towards a new equilibrium. While the results of examining intraday and daily data were not always consistent, the study did empirically examine measures of efficiency and concluded that the open-outcry market has become more efficient with side-by-side computer trading. These results are similar to Tse and Zobotina (2001) who conclude that electronic trading should complement, but not replace, the open-outcry market. My study arrives at a similar result that the market is more efficient with the addition of side-by-side electronic trading.

While the empirical analysis of the efficiency of the market is essential, examining the reasons why the market is more efficient is also important. As discussed in Frino, Harris, McInish and Tomas III (2003) the traders in the pit have monopoly power and they are able to price discriminate. By putting computer trading side-by-side, the CBOT took away some of the monopoly power that the pit traders possessed. This may seem to lead to an end of the pits all together because the pit trader is essentially a scalper who takes advantage of monopoly power to create inefficiencies in the market that can be exploited. The pit trader however is still an essential part of the market as a whole. The pit trader holds an important place in the market, because it provides a unique setting that is very different from the computer, and may even be more efficient at times. Tse and Zobotina (2001) conclude that while computer trading is cheaper to run it

does not always provide the best price for the customer, therefore computer trading should not replace the pits yet. Specifically in the case of the “Dow mini” contract, customers wanting larger sized orders would have to go through a broker in the pit, because the mini is too small a contract. For this reason the pit trader has continued to be essential. Now with the opening of the computer traded “Big-Dow” contract, it seems that the role of the pit trader is declining further.

The pit trader has been the major player in the markets at the CBOT for a long time (the CBOT opened in 1848), but it seems that the once powerful market maker is disappearing. This can be seen in the decline in the number of day traders who use to do very well in the pits. With the emergence of side-by-side computer trading, outcry traders are no longer able to scalp the market like they once did. Rather, the pit trader has become more like a day trader having to take positions that may or may not go in his/her favor. Also spreading and scalping against the other Dow markets, i.e. the “Dow mini”, has become an important part of the survival of the pit trader. While side-by-side computer trading leads to a more efficient market it eliminates a number of traders who were making a living off of those market inefficiencies. The market power of the pit traders as discussed in Frino *et al* (2003) has been greatly limited.

The recent purchase of the CBOT by the Chicago Mercantile Exchange (Merc) makes the future of the pits even more interesting. The Merc is in process of moving all of its pits to the CBOT building, and reconfiguring all of the pits at the CBOT and the pits from the Merc into one trading floor. The future of the pit trader is uncertain, to say the least. As computer markets become more and more efficient, there will be fewer inefficiencies for the pit trader to capitalize on.

This study has its shortcomings but it was able to show, through examination of the Dow Jones futures open-outcry market, that the introduction side-by-side computer trading has produced a more efficient market. Market efficiency, most commonly looked at by examining the bid-ask spread, is difficult to analyze if the market, like the CBOT, does not quote the actual spread. This examination, using estimators, applies the methods from previous studies to a different market than had been examined previously. The CBOT markets are very different from other markets. Though the results of this study are mixed it did produce very similar results to Cheng *et al* (2005) for the regressions. The conclusion is that the open-outcry market is more efficient with the addition of side-by-side computer trading. Computer trading eliminates some of the monopoly power and lowers the transaction costs for outside investors.

Further research is needed in a number of areas in order to expand on this empirical analysis. The first area is more examination of bid-ask spread estimators. This is a hurdle that will probably never be completely overcome in the study of the CBOT because only time and sales data are available. More research is needed on moments estimators. It maybe helpful to use similar methods but instead use a moments estimator for the spread.

Another area where this study can be expanded is the sample size. While the data as a whole are very large, and difficult to deal with, it is important to include more data to get a better understanding of the market. Expanding this analysis to include the examination of both computer trading data and open-outcry data⁹ to show how efficient the computer trading market is compared to the open-outcry market, would be interesting.

⁹ This study only used open out-cry data.

The two markets are probably somewhat similar because trading is being done side-by-side but it would be helpful to examine this empirically.

References

- Alibo, Evamena and Owain Gwilym. "Decreased Price Clustering in FTSE 100 Futures Contracts Following a Transfer from Floor to Electronic Trading," *The Journal of Futures Markets*, Vol. 23, No. 7, (2003) 647-659.
- Beales, Richard, Joanna Chung and David Turner (2005, December 14). "A Traders Nightmare." *Financial Times*, December 14, 2005 Pg. 28.
- Cheng, Kevin, Joseph Fung and Yiuman Tse. "How Electronic Trading Affects Bid-Ask Spreads and Arbitrage Efficiency Between Index Futures and Options," *The Journal of Futures Markets*, Vol. 25, No. 4, (2005), 375-398.
- Fama, Eugene. "Efficient Capital Markets: A Review of Theory and Empirical Work," *Journal of Finance*, May 1970, v. 25, iss. 2, pp. 383-417.
- Frino, Alex, Fredrick Harris, Thomas McInish and Michael Tomas III. "Price Discovery in the Pits: The Role of Market Makers on the CBOT and the Sydney Futures Exchange," *The Journal of Futures Markets*, Vol. 24, No. 8 (August 2004), 785-804.
- Frino, Alex, Jarnecic, Elvis, Johnstone, David and Lepone, Andrew. "Bid-Ask Bounce and the Measurement of Price behavior Around Block Trades on the Australian Stock Exchange," *Pacific-Basin Finance Journal*, 13 (2005) 247-262.
- Fung, J. K. W., & Mok, H. M. K. "Index Options-Futures Arbitrage: A Comparative Study with Bid-Ask and Transaction Data," *Financial Review*, 36, (2001), 71-94.
- Greimel, Hans. "Botched Stock Trade Costs Japan Firm \$225M". Associated Press, *Business News*, December 9, 2005.

- Holder, Mark and Sinha, Amit K. "Bid-Ask Spread Determinants in Treasury Note Futures Contract at the Chicago Board of Trade," October 4, 2004. Accessed at <http://business.kent.edu/MSFE/pdf/Holder%20-%20BidAsk%20determinants%20jun%2004.pdf>.
- Huang, Roger. "The Quality of ECN and Nasdaq Market Maker Quotes," *Journal of Finance*, Vol. 57, No. 3. (June 2002), 1285-1319.
- Hull, John C. *Options, Futures, and Other Derivatives*. 5th Edition. Upper Saddle River, NJ: Prentice Hall, 2002.
- Roll, R. "A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market," *Journal of Finance*, 39, (1984), 1127-1139.
- Smith, Tom and Whaley, Robert. "Estimating the Effective Bid-Ask Spread from Time and Sales Data". *The Journal of Futures Markets*, Vol. 14, No.4, (1994), 437-455.
- Taylor, Nick, Dick van Dijk, Phillip Hans Franses and Andre Lucas. "SETS, Arbitrage activity, and Stock Price Dynamics," *Journal of Banking and Finance*, Vol. 24 (2000), 1289-1306.
- Tse, Yiunan. "Market Microstructure of FT-SE 100 Index Futures; An Intraday Empirical Analysis," *The Journal of Futures Markets*, Vol. 19 No. 1 (1999), 31-58.
- Tse, Yiunan and Tatyana Zabolina. "Transaction Costs and Market Quality: Open Outcry Versus Electronic Trading," *The Journal of Futures Markets*, Vol. 21, No. 8, (2001), 713-735.
- Wang, Jianxin. "Asymmetric Information and the Bid-ask Spread: an Empirical

Comparison Between Automated Order Execution and Open Out-cry Auction,”
Journal of International Financial Markets, Institutions and Money, Vol. 9
(1999), 115-128.