How Market Makers Affect Efficiency;
Evidence Markets are Becoming Less Efficient.

Kurt W. Rotthoff*
Seton Hall University
Stillman School of Business

October 2009

Abstract:

Stock exchanges around the world have integrated a hybrid trading system. This has added anonymity for traders, making it harder for market makers to match large continuous trades, leading to an increase in volatility and a decrease in efficiency. This occurs because less information is contained in the price of a stock at any given time. Using a relative difference-in-difference estimation I find that as the hybrid market was adopted market volatility increased (for both the NYSE and LSE) relative to an electronic market. Although the use of a hybrid market may increase transaction speed, it decreases informational efficiency.

JEL Classifications: G12, G14, G15
Keywords: Market Efficiency, Hybrid Market, Information Efficiency, Speed Efficiency

---

* Kurt Rotthoff at: Kurt.Rotthoff@shu.edu, Seton Hall University, JH 621, 400 South Orange Ave, South Orange, NJ 07079 (phone 973.761.9102, fax 973.761.9217). I would like to thank Mike Maloney, John Warner, Bruce Yandle, Brian Henderson, Tina Yang, Gemma Lee, Angela Dills, Patrick McLaughlin and Hillary Morgan. Any mistakes are my own.

1. Introduction

In recent years the New York Stock Exchange (NYSE) and the London Stock Exchange (LSE) developed a hybrid market that merged the long time outcry, or auction, market with an online trading platform. The hybrid market is designed to give traders quicker transactions and increased ability to search for the best price and anonymity. Because markets are a continuous sequence of bilateral transactions occurring throughout the day, the hybrid design and the exchanges' adoption of it has increased the speed at which transactions can take place. However, as transaction speed increases, this does not necessarily increase the information imbedded in the price at any point in time.

Market makers, formally known as specialists or designated market makers on the NYSE, have long been involved in the trading process. Because on different exchanges they can have different titles, in this work I use the term "market maker" in the most general sense. The term market maker is used as a person who is out to make the market transactions work more efficiently by providing liquidity in the market. The analysis of their involvement of the trading process is vital as technology increases the speed in which transactions occur. This work tests the effects of removing these market makers from the transactions. Looking at Figure I, the measure of volatility in the markets before and after they move to a hybrid system reveals information on the value market makers bring. This ultimately determines if there is a loss in informational efficiency as the market makers lose their ability to provide liquidity in the market.

In the past, market makers would provide bid/ask spreads as the random arrivals of orders were processed. However, as the hybrid system was adopted, the market maker's role changed. Today they provide some liquidity by quoting bid and ask spreads; however most liquidity comes from random arrivals of buy and sell orders through an electronic system. This works to increase the speed and accuracy at which prices are updated. If companies are going to make buy or sell orders, large enough for price movement, the order is divided up as to not influence the price.[1] Some work has used price spreads (ex. Bessembinder, Hao, and Lemmon 2007) as a measure of efficiency and others use deviations from the random walk (Boehmer and Kelly 2009) to reveal relative informational efficiencies in prices. I expand upon this research by using relative volatility as a measure of informational efficiency. Prices are determined at any point in time by the most recent transaction. The volatility of these transactions show the changes in price over time. The use of relative volatility will reveal whether different markets have different price movements as different systems are used. Although previous works have not used volatility in this way, it has not been excluded as a way to measure efficiency.

Before the hybrid system, as large continuous orders came in, market makers had the ability to match large orders as long as there were two trades in opposition. However, the introduction of the hybrid system brought trade anonymity, not only to other investors and companies, but also to the market makers. This means large continuous orders can be sent without revealing the identity of the buying or selling party, which reduces the market maker's ability to stabilize the price. Another way to describe the loss of price

[1] It is possible for these orders to be taken to the upstairs market, but not as appealing because electronic markets have increased anonymity, meaning large trades can be taken to the floor of the exchange in order to hide the transaction from other investors or companies.

stabilization is as an increase in volatility. Because market makers can no longer match large orders under the hybrid system, we should observe an increase in volatility because at any given point in time full information about the trading process is not imbedded in the price of that stock. This increase in volatility reflects a loss of information in the security's price, or a loss of efficiency. The main contribution of this paper is to show that although technology has increased speed efficiency, informational efficiency has decreased, as measured by relative volatility in price movement.

Figure I:

Although "the speed of the trading mechanism has long been an important dimension of financial market design… the growth of electronic trading in recent years has intensified the emphasis on speed" (Hendershott and Moulton 2009). There has been a focus on the speed increase in the literature, however this study continues to look at the effects of this speed increase. Figure I shows the monthly standard deviation of the NYSE and the LSE six months before and after the changes to the quasi-hybrid and hybrid markets. I will test if there is a loss in efficiency by examining the changes in volatility over time as the NYSE and LSE move from an auction system to a hybrid format. This is tested using four methods: a variance ratio test, rolling window test, event study, and GARCH estimation (plus two robustness checks). The next section discusses the implications of having market makers in the transaction process followed by section three giving a brief background of the market systems. Section four discusses the methodology and section five explains the data and results. Section six concludes.

2. Market Makers

Market makers have been an integral part of the trading process. Ellul (2000) finds that the use of dealers in hybrid markets help stabilize prices. Gromb and Vayanos (2002) and Weill (2009) state that the liquidity provided is a public good with positive externalities. Other research has also supported the existence of market makers, finding that introducing market makers where they previously had no presence may be good (Nimalendran and Petrella 2003), which arises because market makers can fill gaps appearing from unbalanced order arrivals (Demsetz 1968). Work by Garabade and Silber (1979), Grossman and Miller (1988), and Venkataraman and Waisburd (2007), show that market makers reduce the temporal imbalances in order flow by maintaining a market presence. This research has continued in electronic markets and their use of market makers (Bessembinder, Hao, and Lemmon 2007). A more specific example of market makers involves Merck and the drug Vioxx. On September 30, 2004, the morning after the announcement of the withdrawal of Vioxx, market makers at the NYSE stepped in to make the market for Merck. There were approximately five million shares set to be sold at the open that morning, but only four and a half million buy offers. Market makers not only made the market that morning, they arguably were close to the correct price: opening the day at $33.40 a share and closing at $33.00.

A common argument in support of electronic markets is that the electronic aspect increases liquidity. Chordia, Roll, and Subrahmanyam (2008) find that liquidity, which is increased by the electronic market, stimulates arbitrage activity. They further claim that liquidity enhances market efficiency by defining efficiency as the gain in speed enjoyed by arbitrageurs who can imbed information about the price more quickly. The basis of my study revolves around this point: although the information transfer is faster in an electronic market, the total amount of information in the price at a given point in time may not be the same. The information previously brought by the market makers is no longer present, meaning informational efficiency is decreasing despite the increase in speed efficiency.

Market efficiency implies that all available information is imbedded in the price of the stock. Since Fama's (1970) work showing that markets are quite efficient, many have studied the effect of efficiency, and/or lack of it, in different markets and over different time intervals. Early works (Hillmer and Yu 1979, Epps 1979, and Patell and Wolfson 1984) have shown that markets are quite efficient, but more recent studies have examined efficiency over short periods of time with different results. Cushing and Madhavan (2000) and Chordia, Roll, and Subrahmanyam (2005) find that over short time horizons, past order flow can predict returns, implying a lack of efficiency. Because markets are continuous, prices are continually revised to reflect new information, implying efficiency is a process. Therefore, the process in which prices become efficient can not be separated from an asset's price at any specific moment. Rather than look at an asset's price at a point in time, this study uses a relative difference-in-difference test to measure how asset prices move over time.

Venkataraman and Waisburd (2007) find that there are potential benefits associated with designated market makers. They also point out that a problem arises when market makers are absent because buyers and sellers are not perfectly synchronized. This paper looks at the ability of market makers to alleviate the synchronization problem. As stated before, market makers have the ability to combine large, consistent, buy (sell) orders with matching sell (buy) orders. However, as the hybrid system is introduced, their ability to do this diminishes. In the time after adoption of the hybrid system, it should be observable that the price volatility increases because large orders can no longer be matched. An increase in volatility, after controlling for changes in variation over time, represents a loss in informational efficiency. To test if there is a loss in efficiency I examine the changes in volatility over time by comparing the NYSE and LSE as they move from auction systems to hybrid systems.

The next section will give a brief history before the methodology is discussed in section four.

3. Background

In the last decade, stock markets around the world have been initializing trading floors with integrated technology. Stock markets like the NYSE and LSE, are using technology that allow trades to be made either on the floor of the stock exchange, in a live auction market, or through an electronic trading market. As electronic trading has increased, the use of floor traders has decreased. For the NYSE, from the first quarter in 2006 to the first quarter in 2007 there was a 49% decline in the number of traders on the floor.[2]

[2] From the USA Today article 'Technology squeezes out real, live traders', July 12, 2007. http://www.usatoday.com/money/markets/2007-07-11-nyse-traders_N.htm

Using the hybrid system allows stock orders to be sent to the floor for auction trading or sent directly into the electronic market. The hybrid system is explained best in the NYSE Hybrid Market Training Program (September 2006):[3] "The NYSE Hybrid Market is a new market model that integrates the best aspects of the auction market with automated trading. As a result, customers receive the broadest array of trade-execution choices. The Hybrid Market expands customer ability to trade instantaneously with certainty and anonymity without sacrificing the price improvement and market quality of the floor-based NYSE auction market." The new system has been established to allow for more flexible, faster trades while maintaining the best price for both buyers and sellers.

During the development of the hybrid system, the NYSE worried about liquidity and traders' connectivity. To help alleviate the concern, the NYSE set up Liquidity Replenishment Points (LPRs). The LPRs were created to "help curb wide price movements resulting from automatic executions and sweeps over a short period of time."[4] The NYSE also established an Application Programming Interface (API) that allows market makers to connect with specialist firms through the NYSE system. This system was created to ensure fairness, but as a result, the market makers cannot identify the firms entering an order, customer information, or an order's clearing broker. With these changes, floor brokers can use the auction market or, via their handheld devices, make electronic trades through the API without revealing their identity.

The Hybrid market:

- Increases speed of order execution
- Increases the possibility for price improvement
- Increases anonymity
- Allows for pegging (keeping interest in a quote after it moves)
- Allows for sweeps (buying/selling all the open positions at a given price and moving to the next best price instantly)

As the NYSE and LSE have become increasingly electronic, others have been, and remain, electronic throughout their existence. In 1971 the National Association of Securities Dealers (NASD) made an electronic quotation system called NASDAQ available to dealers and brokers. National Association of Securities Dealers Automated Quote System (NASDAQ) was set up as an online trading platform, for which orders can be made, and processed, electronically. This set-up is drastically different from the set-up of the NYSE, or LSE, which was an auction market, a place where traders met and called out buy/sell orders. Before the hybrid market was introduced, trades were matched between the traders and directed by a market maker. When an order lacked a counterpart, the market maker would step in to make the transaction at a reasonable price.

It is widely believed that an electronic market is more volatile than a dealership, or auction, market (Pagano and Roell 1992, Madhavan 1992 and Theissen 2002). But Theissen (2002) also finds that floor trading offers more competitive spreads than screen trades for less liquid stocks on the German Stock Exchange. Nimalendran and Petrella (2003) find that the transition from a pure limit-order system to a hybrid system, with a

[3] http://www.nyse.com/pdfs/hm_booklet.pdf
[4] Also from the NYSE Hybrid Training Program, September 2006.

specialist, increase thinly-traded stocks liquidity on the Italian Stock Exchange. Lai (2007) says “a dealership market is better to cope with ‘difficult’ times than a hybrid market.”

The role of market makers has changed as the regime switched from a quote driven market, where market makers are obligated to provide liquidity, to an order driven market where they are not obligated to do so (discussed in Galariotis and Giouvris 2007). However, not all markets are going through this transition. Because the NASDAQ was established as the world’s first electronic stock market, investigating how the volatility changes relative to a market going through the transition reveals information on the effects of the switch to the hybrid system. (A detailed timeline for the market switching, NASDAQ, NYSE, and LSE, can be found in Appendix A)

4. Methodology

To look at market efficiency, it is vital to understand how the markets are changing. As discussed, some markets have recently been shifting from an auction market to an electronic trading system. The NYSE and LSE have moved to a hybrid system, but before calling it a hybrid system they both went through an integration process with a system consisting of partial floor trading and partial electronic trading. The LSE handled this through their SETS system, which Galariotis and Giouvris (2007) called a quasi-hybrid system. Because there was a quasi-hybrid system and a hybrid system, I test the effects when these markets first initiated electronic trading, or moved to a quasi-hybrid market, and when these markets officially move to a hybrid system. These markets were changing regimes at different points in time, and it is therefore testable to see how these markets respond to the changes in the trading regime.

It is commonly thought that the technological innovation allows for information to travel more quickly, making things more efficient. As new technologies are integrated into the trading platforms, transaction speed has increased. This means things are getting faster, increasing speed efficiency and liquidity. However, if the market makers have less, or no, ability to match large continuous orders, less information is being built into the price of a stock at any point in time. This, by definition, is making the market less efficient. This study tests the market makers’ inability to match orders, due to the establishment of the hybrid system (or a quasi-hybrid system), affects informational efficiency (as opposed to speed efficiency).

A simple example explains the concept effectively: There are many traders, assume we have two with very large orders for the same stock. Company B is a net Buyer of a given stock and Company S is a net Seller of that same stock. Both of the companies are making trades large enough to move the price, so they choose to make their trades in smaller lots over a period of time, as to not influence the price. Traders also choose to avoid the upstairs market because their identity would be revealed. If both of these companies are trying to execute orders over the same period of time, matching these orders can be valuable and can decrease volatility in the stock. As the markets begin to run on a hybrid system, the ability for market makers to match these orders is decreased. When simultaneously combined with increased transaction speed, the probability that any given order matches another order as it is submitted decreases. If orders are less likely to be matched, it is expected that the volatility of the stock will increase.

As Kyle (1985) sets up, "trading takes place over a trading day, which begins at time t = 0 and ends at time t = 1." Because there are many auctions occurring over the day, t_n denotes the time at which the n-th auction takes place. When trades happen slowly, the probability that any given trades will match is high (or as market makers have the ability to help match these trades), but as speed increases this probability falls. As with the example of large trades, stated earlier, the probability of these trades matching falls as the speed of trading increases. This in turn implies that the value of including a market maker involved in the trade increases.[5] It can be argued that this also implies that market makers need to develop ways to handle these transactions without impeding speed, but this issue is left to a future study.

Along with two robustness check, there are four different tests to verify the hypothesis that the electronic markets increase volatility and thus decrease informational efficiency.

a. Variance Ratio Test
b. Rolling Window Test
c. Event Study
d. GARCH
e. Robustness Tests

For the Rolling Window Test and the GARCH estimation, I use a variation of a difference-in-difference (DID) estimation. The traditional DID model is set up by:

$$[(\text{treated group})_{t+1} - (\text{control})_{t+1}] - [(\text{treated group})_t - (\text{control})_t] \qquad (1)$$

Equation 1 sets up a DID estimation where the variable of interest is the coefficient for the given group over the change in time. However, in this paper I am looking at variation, so I am not measuring the changes in the coefficients themselves, but rather the changes in the volatility (standard deviation) of the coefficients. Because of this difference, I am not able to find the statistical significance when testing the difference; I am only able to show trends in the data as the regimes change.

Although the DID set-up tests the difference through subtraction, it can also be measured, in a relative sense, as a percentage change. This means that a relative difference can be measured through division. As an example, if the standard deviation for two regimes are .04 and .06, the difference is .02. In addition, if the standard deviations are .02 and .04 the difference is also .02. Using an absolute measure of difference, subtraction, they show the same change, but in percentage terms the difference between these two are not the same .04 is 67 percent of .06, whereas .02 is 50 percent of .04. In order to measure the relative difference in these two numbers, it is more accurate to measure the percentage difference, rather than the absolute difference. It is for this reason I is use a relative difference-in-difference (RDID) measure (equation 3 below) for the rolling window and GARCH test.

[5] This also benefits those making the large trades. If Company B is a net buyer, then buying the stock drives the price up. If they are able to match with Company S, a net seller, they can maintain price stability, meaning they have the ability to buy at a price that is not inflated and vice-versa.

It is important to note that these tests have three possible outcomes: Support the hypothesis, Refuting the hypothesis, or Neither supporting or refuting the hypothesis (because the results are insignificant or mixed). So for each test, for both the NYSE and LSE, I will report if the test Supports, Neither, or Refutes the effects of the regime switch on informational efficiency.

a. Variance Ratio Test

Lo and MacKinlay (1988) use a variance ratio test to measure if markets follow a random walk. This study uses a similar variance ratio test. I measure the difference over time to test the absolute variance change over time. Measuring in this way allows the separation of time and random effects from the regime switch. Using a matching system, matching a changing regime (the NYSE or LSE) to a regime that does not change (the NASDAQ), reveals information on the effects of the change to a hybrid system relative to a system that does not change.

$$X_t = \mu + \beta_0 X_{t-1} + \varepsilon \qquad (2)$$

Following Lo and MacKinlay (1988), to measure the volatility, X_t denotes the log of the value of the index at time t. Where X_t is found by equation 2, this sets up X_t to be a random walk parameter with a drift (μ) and random disturbance (ε_t). The test is whether $\sigma_i^2 = \sigma_j^2$, where i is the NYSE or LSE and j is the NASDAQ, over a period of time, or the measure of how the σ_i^2 changes relative to σ_j^2 as the regime changes. The theory established in this study states that in the absence of the hybrid market $\sigma_i^2 \neq \sigma_j^2$, but when the hybrid market is present σ_i^2 approaches σ_j^2. The standard deviations will be converging, and not necessarily be equal, because although the hybrid market is used, there still are some trades made on the floor. It is also important to note that different markets trade different assets, which implicitly may have different underlying variances.[6] For this reason, it is the relative change in the variation that reveals information about the effects of moving to a hybrid market.

b. Rolling Window Test

To confirm the results found in the variance ratio test above, I use a rolling window estimation of the variances. This means that instead of conducting a test over the whole sample, or a single year at a time, I look at the variance for days 1-50, then again for days 2-51, 3-52, and so on. The variance used is the average measure found for each 50 day window throughout any given period or regime. These periods are split by the change in regime, and set time periods before and after the switch are compared to see if the variances change as the regime changes. Because variance increases over time in a stochastic process, measuring the 150, 300, or 450 trading days before and after the switch provides the needed information for this test.[7] This rolling window setup allows

[6] I assume although they have different assets, their assets are similar over the sample.
[7] These day ranges involve oversampling issues which are addressed in the robustness section.

the use of an average variance for each 50 day window over that period, providing a more focused measure of the effects of the regime switch.

The average standard deviations for each of these 50 day windows is then compared before and after each regime switch as an RDID:

$$\frac{\sigma : X_A / \sigma : NASDAQ_A}{\sigma : X_B / \sigma : NASDAQ_B} \tag{3}$$

Where σ:X_B is the standard deviation on the NYSE, FTSE100, or FTSE250 before (B) the regime switch and σ:$NASDAQ_B$ is the standard deviation on the NASDAQ before X had a regime switch. σ:X_A is the measure of the switching regime's standard deviation after (A) the switch, with σ:$NASDAQ_A$ being the standard deviation on the NASDAQ after the switch.

Equation 4 represents the standard deviation in X (NYSE or LSE) divided by the standard deviation in the NASDAQ, both before the regime switch.

$$\sigma : X_B / \sigma : NASDAQ_B \tag{4}$$

If equation 4 is less than one, the standard deviation of the NASDAQ is larger than the given stock exchange. Equation 3 takes this into account and measures the relative difference in the standard deviation before and after the switch. Therefore, if equation 3 is greater than one, the difference in the standard deviations between the switching regime and the non switching regime (NASDAQ) is smaller after the regime switch. This shows that the switching of regimes, from an auction to a quasi-hybrid or a quasi-hybrid to a hybrid market, is causing the standard deviation of the changing market to converge in measure, in terms of variation, to the all electronic market. Given equation 3 is greater than one, this supports the hypothesis that as markets change to a hybrid trading market, volatility is increased and information is lost.

c. Event Study

After setting up the variance test, I can use information on the standard deviations to create a data set of monthly standard deviations for each index. With this data, an event study can be used to test the effect of moving to a quasi-hybrid, or hybrid, market. A dummy variable is set up for when the exchange is using a form of a hybrid system, or when they integrate some from of electronic trading system.

$$\sigma\text{: } X_t = \beta_0 + \beta_1\ \sigma\text{: } NASDAQ_t + \beta_2\ (Electronic_t) + \varepsilon \tag{5}$$

Equation 5 is the regression of each of the exchange's standard deviations X_t, by month, on the standard deviation on the NASDAQ and a dummy variable for the type of market. The electronic dummy is 0 during the auction market (quasi-hybrid market) and 1 for the quasi-hybrid market (hybrid market), done separately. If β_2 is significant and positive it shows that the volatility of the changing market is higher, controlling for the market that does not change, during the electronic platform. This regression is done again with monthly dummies to control for seasonal effects in the market. Given a positive, and statistically significant, coefficient on β_2, this supports the hypothesis of a loss in efficiency.

d. GARCH

As is standard in time series variance measurement (Engle 2001), I also use GARCH (Generalized Autoregressive Conditional Heteroskedastic) estimation. The use of GARCH allows the contingent volatility to be measured, rather than the absolute volatility, which is used in the variance tests above. Since Engle (1982) introduced the ARCH model, which was then generalized by Bollerslev (1986), these specifications have been used to capture most of the volatility clustering and serial correlation in time series data. This has allowed finance data to be analyzed more accurately through conditional variance modeling. Instead of worrying about the existence of heteroskedasticity, I use a GARCH estimation model:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \, \varepsilon_{t-1}^{\;2} + \beta_1 \, \sigma_{t-1}^{\;2} \tag{6}$$

Where the $\varepsilon_{t-1}^{\;2}$ follows the ARCH setup in Engle (1982) and the $\sigma_{t-1}^{\;2}$ follows the GARCH setup in Bollerslev (1986). As Nelson (1992 and 1995) points out, the set-up of the GARCH model matters. Starting the lagged variables at different points can give different results. Because of this, I use 150, 300, and 450 trading day windows, both before and after each of the regime changes. Using the different windows eliminates any specific effects that arise from choosing certain start dates. Allowing the start date to change reveals more information about the true effects over time. In addition, I match the standard errors (the standard deviation isn't reported in GARCH), as an RDID (equation 3), to test if GARCH reports estimations greater than one. A result that is greater than one supports the idea of a loss in informational efficiency.

e. Robustness

To check if the results are robust, I will first look at the issue of limited data. When testing the regime switch, the available data is limited because both of the exchanges change only once. Because of this limitation, oversampling methods are used to increase the data available in both the rolling window test and the GARCH test. A correction is needed because in using the different window lengths (150, 300, and 450), a double counting of observations occurs. For example, the 300 window has 300 days, of which the first 150 days are already included in the 150 day test. Following the works by Hansen and Hodrick (1980), Amihud and Hurvich (2004), and Henderson, Jegadeesh, and Weisbach (2006) I address an alternative set-up to control for the sample bias.

Given a regression in the form:

$$y_t = \alpha + \beta \cdot x_{t-1} + \varepsilon_t \tag{7}$$

and using an independent variable that follows an AR(1) process:

$$x_t = \theta + \rho \cdot x_{t-1} + \upsilon_t \tag{8}$$

The β is biased downwards if the cov(ε_t, υ_t) > 0 (Stambaugh 1999). However following Amihud and Hurvich (2004) and Henderson, Jegadeesh, and Weisbach (2006) the corrected estimator follows:

$$\hat{\rho}^c = \hat{\rho} + (\frac{1+3\hat{\rho}}{n}) + (\frac{3+9\hat{\rho}}{n^2}) \tag{9}$$

This constructs the estimator controlling for sample size, where *n* is the sample size. Because I am measuring the variation of these indexes, rather than estimating a coefficient, I need to use a different measure as a proxy for the correction. To test for an oversampling problem I test for a bias in the 150 day overlap. This reveals if the first 150 days are driving the results in the rolling window and GARCH tests, or if the volatilities continue to converge after the new regime is in place.

It is also important to note that because I am comparing different stock markets, the NASDAQ, in general, has different stocks on its market than the others. As stated in Amihud and Mendelson (1987, page 534) "the difficulty with empirical comparison is that different markets trade different assets and these assets are traded in different environments". Although the exchanges have different stocks, they tend to be consistent over time, so the use of an RDID separates out the trading in different environments, or the regime switches, from the different assets. Nevertheless given that results could be driven by differing equity types, as a second robustness check I will match similar stocks on the different exchanges to see if the results from the previous tests hold.

The initial move to a quasi-hybrid market occurred during the tech bubble, while the switch to a hybrid market occurred during the beginning of the financial crisis. These two events, in addition to the different equity types on the different exchanges, could give spurious results and cause problems with the data in both the placebo group (NASDAQ) and the comparison group. To make sure that the results are not driven by either of these problems I will construct a matched sample of companies in the S&P 500 index. I will match companies using a one-to-one matching system, matching companies that are a) in the S&P500 during the sample, b) have similar market capitalizations, and c) have similar productions (according to their SIC, Standard Industrial Classification, Codes).

In this data I include all stocks that have consistently been in the S&P500 from 2000 to Fall 2009, leaving 299 total stocks, 39 of which are Financial stocks with 5 successful matches and 37 of which are Information Technology (IT) stocks with 12 successful matches. Matches are made according to two-digit SIC codes and market capitalization.

Using 5 Finance matches and 12 IT matches, independently, I will average them and use equation 3 to check if these two industries, and the markets they are traded on, are driving the results. This will test if the tech bubble, the financial crisis, and the exchanges, trading different equities, are driving the results found in the above tests.

$$\frac{\sigma : NYSE_{A;i,j} \big/ \sigma : NASDAQ_{A;i,j}}{\sigma : NYSE_{B;i,j} \big/ \sigma : NASDAQ_{B;i,j}} \tag{10}$$

In equation 10, σ:NYSE is the average standard deviation of the stocks in the Finance (*i*) and Information Technology (*j*) sectors traded at the NYSE and σ:NASDAQ is the average standard deviation of those stocks traded on the NASDAQ. This measures the RDID in standard deviation before (*B*) and after (*A*) the regime switch. Following equation 3, if equation 10 is greater than one, the difference in the standard deviations between the switching regime (NYSE) and the non switching regime (NASDAQ) is smaller after the regime switch. This shows that the switching of regimes, from an auction to a quasi-hybrid or a quasi-hybrid to a hybrid market, is causing the standard deviation of the changing market to converge in measure, in terms of variation, to the all electronic market. Given equation 10 is greater than one, this supports the hypothesis that as markets change to a hybrid trading market, independently of equities or current crises.

5. Data and Results

This study uses data from Bloomberg on the NYSE composite index, NASDAQ composite index, as well as the FTSE100 and FTSE250 indexes. Data is used from April 1986 through the end of February 2009. These data include both before and after the implementation of the hybrid (and the quasi-hybrid systems) for the NYSE and LSE (FTSE100 and FTSE250). Recall that the NASDAQ remains an entirely electronic system throughout the sample. I have information on the high and low price of the indexes over this period and use this information to look at the standard deviation in the log (price) over time. Utilized throughout the study, the availability of this high/low data doubles the number of observations because a high and low value is observed for each day. The use of this high/low data gives a more accurate measure of the variation over the time period.

Each index is broken down into the four possible categories: All electronic, Hybrid, Quasi-Hybrid, and Auction (Human). It is the separation of these four categories, and how the standard deviation changes as the market type changes, that is measured. The following figures show the standard deviations of the different markets (NYSE, FTSE100, and FTSE250) relative to the NASDAQ. The dashed vertical line shows when the market went to a quasi-hybrid system, whereas the solid vertical line is where the market officially went to a hybrid market.

Figure II

Figure III

Figure IV

Below, table one shows how the variation changes over time, because it is not possible to tell from the charts above if the change in trading platform has any effect. To first examine the regime switch I start by looking at the average number of times a month that the index changes 2% or more, in a given day, under different market structures.

Table I

When looking at the average number of times a month that the index moves more than 2% in one day, it increases over time, which is expected because stochastic processes tend to increase in volatility as the series continues. As seen in Table I, the number of times this happens increases as markets change their trading platform, but this does not reveal any insightful information about the switch to a hybrid market because the time effect has not been separated out.

a. Variance Ratio Test

The Variance Ratio Test will compare standard deviations over time. The first set of data reported is the standard deviation from the High and Low price each day, by year (Table II).

Table II

For the variance ratio test, the f-statistic for equation 2 is reported in Table III.

$$\text{Ratio of } \frac{\sigma : x}{\sigma : NASDAQ} > 1 \tag{10}$$

Table III

The results from the variance ratio test do not show convincing results for or against the hypothesis that as markets change to a hybrid system, information is lost and volatility is increased. I now approach the issue using a rolling window test.

b. Rolling Window Test

For the rolling window variance test, a 50 day window is used. This means that for the time period in the study, standard deviations are estimated for the first 50 days, then days 2-51, 3-52 and so on. Therefore, the standard deviation reported is the average standard deviation for all 50 day windows in each time period. The time periods used are 150 days, 300 days, and 450 days before and after the regime switch. Recall that because the High/Low data has the observations listed separately, there are 300 observations to encompass 150 days, 600 observations for 300 days, and 900 observations for 450 days.

To test the effect of the change in regime, I use an RDID:

$$\frac{\sigma : X_A \big/ \sigma : NASDAQ_A}{\sigma : X_B \big/ \sigma : NASDAQ_B} \qquad (3)$$

Equation 3 is greater than one when the regime switch causes the variation to increase relative to the NASDAQ market. In tables IV, V, and VI, the last column indicates whether or not the switching of regimes from an auction to a quasi-hybrid, and a quasi-hybrid to a hybrid market, is causing the standard deviation of the changing market to converge in measure to the all electronic market.

Table IV

Table V

Table VI

From the three tables above (tables IV, V, and VI) there is little significance found in the FTSE250, which is not a surprise. The FTSE250 began to shift their stocks to a hybrid system before it was official for all stocks on that index, whereas the other markets switched more unanimously. Because of the soft data on the date of the regime switch, picking up the true effect of the switch on the FTSE250 is difficult. However results are present for the NYSE and FTSE100. The NYSE had a significant impact on the move to a hybrid market, but not from the switch to the quasi-hybrid market. The FTSE100 has strong results showing that as the market has become more electronic, volatility has been increasing. The results on the NYSE and FTSE100 show that a regime switch does have an effect on the variance within the markets, supporting the hypothesis.

c. Event Study

From the variance ratio test, I have the monthly standard deviation for each exchange in the data. I have created a dataset that includes all standard deviations, by month, for each of the exchanges (NASDAQ, NYSE, and FTSE100). Using a dummy variable for the type of market, whether it is a quasi-hybrid or hybrid market, it is possible to see if the electronic market causes an increase in the variation relative to the NASDAQ.

$$\sigma\!: X_t = \beta_0 + \beta_1\ \sigma\!: NASDAQ_t + \beta_2\ (Electronic_t) + \varepsilon \qquad (5)$$

Equation 5 is the regression of each exchange's standard deviation (X), by month, on the standard deviation on the NASDAQ, with a dummy variable equal to one if the market is electronic. The summary statistics for these data are in table VII.

Table VII

Table VIII

Table IX

Table VIII shows the regressions for the event study, on the quasi-hybrid and hybrid systems with no controls for seasonal effects. Table IX shows the same regression but includes monthly dummy variables, as fixed effects, to control for seasonal differences in variation.[8] It can be seen that as the NYSE and FTSE100 go to a hybrid system, the standard deviation is significantly higher, relative to the NASDAQ, than it is during the auction market.[9] However the regression on the quasi-hybrid system is only significant for the NYSE and not the FTSE100. On the whole these results again support the hypothesis that volatility is increasing as markets move to an electronic system.

d. GARCH

To test for the conditional variance over time, the rolling window again is used, by implementing a GARCH estimation. I look at the standard errors (the standard deviation is not reported in the GARCH framework)[10] before and after the move to a quasi-hybrid system as well as a hybrid system, for each 150, 300, and 450 days before and after the event, using a RDID. This tests the conditional variances, rather than the absolute variances.

Table X

Using the GARCH approach for the NYSE (table X), it is found that the 150 day window shows strong support for the theory. However, when using conditional mean measures, the increase in days from the regime switch decrease in the strength of the theory for the switch to the quasi-hybrid market, but continues to support when the NYSE went to the hybrid market.

Table XI

The estimation using a GARCH approach with the FTSE100 (table XI) gives mixed results for the move to the quasi-hybrid market and refutes the theory for the hybrid market.

e. Robustness

As mentioned previously, there are issues with oversampling because of the nature of the data. The use of the rolling window test and the GARCH test use data from 150 before and after the event as well as 300 and 450 days. Because of the set-up, days 1-150 are used in all three of these tests, thus leading to an oversampling problem. Because

---

[8] Yearly fixed effects cannot be used because it takes away the switch in regime effect. This happens because the switch only occurs once over the time periods.
[9] Because the FTSE250 changed its stocks to a hybrid system over a series of time, rather than on a given date, this analysis is not used on that market.
[10] The standard errors can be used in this case because the number of observations is equal in all regressions.

I am interested in variance and not coefficients, at this time, the tests to correct this are limited. However knowing the problem exists means I can test windows excluding the oversampling to see if these days are driving the results. Testing this data for both the rolling window test and the GARCH test, I test the impact of the overlapping time periods, days 151-300 and 301-450.

Table XII

Table XIII

Looking at table XII and XIII there are no definitive conclusions that can be draw when looking at days 151-300 and 301-450 in the data. These results are mixed and weak at best. Because of these mixed results, the robustness tests neither support nor refute the hypothesis for the rolling window test (using the RDID).

Table XIV

Table XV

The results in tables XIV and XV continue to show mixed results for the robustness test on the GARCH model. I interpret these regressions to mean that the overlapping samples have no major impact on the previous tests.

The second robustness test is matching stocks that have been on the S&P500 consecutively by SIC Code and market capitalization produces the following results.

Table XVI

Table XVII

As you can see in tables XVI and XVII the results are supported by the Financial stocks and split for the IT stocks. This test supports the Hybrid market having an effect on efficiency, but gives mixed results for the regime switch to a quasi-hybrid market.

6. Conclusion

There have been two main impacts of markets like the NYSE and LSE moving to an electronic trading platform that have ultimately lead to a decrease in information contained in the price of a stock. The first has been an increase in trading speed, which at first was thought to increase efficiency. However, it is important to separate speed efficiency from informational efficiency. Although trades can be conducted more quickly, this does not imply that the process has become more efficient, it only means it is faster. As trading speeds increase and more transactions are conducted electronically rather than by human traders in the pits, it is harder for market makers to match large orders. The missing matching ability has decreased the information built into the price of any given stock at any given time. Thus, if less information is built into the stock, the market is less efficient.

A second impact of the electronic trading platform has been an increase in anonymity. In part, this information asymmetry comes from large continuous orders that can be sent without revealing the identity of the buying/selling party. When market makers can match large orders, volatility is reduced which implies that the opposite must also be true. As anonymity increases and market makers cannot effectively match buyers and sellers, volatility increases. Under the hybrid system or quasi-hybrid system, increased anonymity, similar to the increase in speed, decreases the amount of information in the price at any point in time.

To test these effects I use four tests of variance over time. These methods analyze the effects of changing a market from an auction system to an electronic system, by utilizing the dates in which a quasi-hybrid or hybrid market was adopted. To test how the variance is impacted, it is important to compare the change relative to something that does not change, which controls for random fluctuation in variation over time. To do this I use a relative difference-in-difference (RDID) approach, comparing the NYSE and LSE to an all electronic market (NASDAQ), measuring the convergence of variation. Note that there are three potential outcomes from these tests; tests can either show Support for the hypothesis, Refute the hypothesis, or have no impact (Neither) on efficiency.

	Results			
Test	NYSE		FTSE100	
	Auction to Quasi-Hybrid	Quasi-Hybrid to Hybrid	Auction to Quasi-Hybrid	Quasi-Hybrid to Hybrid
a. Variance Ratio Test	Neither	Neither	Neither	Neither
b. Rolling Window Test	Refutes	Supports	Supports	Supports
c. Event Study	Supports	Supports	Neither	Supports
d. GARCH	Neither	Supports	Neither	Refutes
e. Robustness	-	-	-	-
1) Oversampling	Neither	Neither	Neither	Neither
2) Matching Data	Neither	Supports		

When testing for the increase in variation of markets as they move to an electronic trading platform, relative to the NASDAQ, the variance ratio test and GARCH tests neither supports nor refutes the hypothesis. However, when using a rolling window RDID test and event study tests the hypothesis is supported. In addition to those tests two robustness tests were done. The first is testing problems of oversampling, finding that oversampling is not an issue. The second test looks at matching specific S&P 500 stocks on the NYSE and NASDAQ exchanges. This test supports that the hybrid change had an impact on efficiency and eliminates the concern that these results are driven by the tech bubble or the financial crisis. With these results I conclude that the movement to an electronic platform increases the volatility in asset pricing. As volatility is increased, it is not possible for me to refute an existing loss in informational efficiency. Market makers provide for more informed markets, and thus more informationally efficient markets. The value of informational efficiency vs. speed efficiency is left for later, or continued, debate.

Works Cited

Amihud, Y., Hurvich, C., 2004. Predictive Regressions: A Reduced-Bias Estimation Method. *Journal of Financial and Quantitative Analysis* 39, 813–841.

Bessembinder, Hendrick, Jia Hao, and Michael Lemmon, 2007. Why Designate Market Makers? Affirmative Obligations and Market Quality *working paper* July, http://www.business.utah.edu/humis/docs/person_1268_1185921801.pdf

Bollerslev, T. 1986. Generalized Autoregressive Conditional Heteroskedasticity *Journal of Econometrics* 31, pp. 307–327.

Boehmer, Ekkehart and Eric Kelly, 2009. Institutional Investors and the Informational Efficiency of Prices *The Review of Financial Studies* Vol. 22, Issue 9, 3563-3594

Chordia, Tarun, Rochard Roll, and Avanidhar Subrahmanyam, 2005. Evidence of the Speed of Convergence to Market Efficiency *Journal of Financial Economics* 76, 271-292.

Chordia, Tarun, Rochard Roll, and Avanidhar Subrahmanyam 2008. Liquidity and Market Efficiency *Journal of Financial Economics* 87, 249-268.

Cushing, D. and A. Madhavan 2000. Stock Returns and Trading at the Close *Journal of Financial Markets* 3, 45-67.

Demsetz H. 1968. The Cost of Transacting *Quarterly Journal of Economics* 82, 33-53.

Ellul A. 2000 The Market Maker Rises Again: Price Volatility and Order Flow Dynamics in a Hybrid Market *Manuscript*, Financial Markets Group (London School of Economics).

Epps, T., 1979. Comovements in Stock Prices in the Very Short Run *Journal of the American Statistical Association* 74, 291-298.

Engle, R. F. 1982, Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation *Econometrica* 50, 987-1006.

Engle, Robert 2001. GARCH 101: The Use of ARCH/GARCH Model is Applied Econometrics *Journal of Economic Perspectives* Volume 15, Number 4, 157–168.

Fama E.F. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work *Journal of Finance* 25, 383-417.

Galariotis and Giouvris 2007. Liquidity Commonality in the London Stock Exchange *Journal of Business Finance & Accounting* 34, 374-388.

Garbade K.D., Silber W. 1979. Structural Organization of Secondary Markets: Clearing Frequency, Dealer Activity and Liquidity Risk *Journal of Finance* 34, 577-593.

Groosman, S., and M. Miller 1998. Liquidity and Market Structure *Journal of Finance* 56, 877-919.

Gromb, Denis and Dimitri Vayanos, 2002. Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs *Journal of Financial Economics*, 2002, 66, 361-407.

Hansen, L. and Hodrick, R., 1980. Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis. *Journal of Political Economy* 88, 829–853.

Hendershott, Terrence and Moulton, Pamela C., Speed and Stock Market Quality: The NYSE's Hybrid (August 5, 2009). *working paper*, Available at SSRN: http://ssrn.com/abstract=1159773

Henderson, Brian J., Narasimhan Jegadeesh, and Michael S. Weisbach. 2006. World Markets for Rising New Capital *Journal of Financial Economics,* Vol. 82, 63-101.

Hillmer, S. and P. Yu 1979. The Market Speed of Adjustment to New Information *Journal of Financial Economics* 59, 253-278.

Kyle A.S. 1985. Continuous Auctions and Insider Trading, *Econometrica* 53, 1315-1335.

Lai, Hung-Neng 2007. The Market Quality of Dealer Versus Hybrid Markets: The Case of Moderately Liquid Securities *Journal of Business Finance & Accounting* 34, 349-373.

Lo, A.W. and MacKinley A.C. 1988. Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test *Review of Financial Studies* 1, 41-66.

Madhavan A., Smidt S. 1991. A Bayesian Model of Intraday Specialist Pricing *Journal of Financial Economics* 30, 99-134.

Madhavan A., Smidt S. 1993. An Analysis of Changes in Specialist Inventories and Quotations *Journal of Finance* 48, 1595-1628.

Nelson, Daniel B. 1992. Filtering and the Forecasting with Misspecified ARCH Models I: Getting the Right Variance with the Wrong Model *Journal of Econometrics* 52, 61-90.

Nelson, Daniel B. and Dean P. Foster 1995. Filtering and Forecasting with Misspecified ARCH models II: Making the Right Forecast with the Wrong Model *Journal of Econometrics* 67, 303-335.

Nimalendran, M. and G. Petrella 2003. Do 'Thinly-Traded' Stocks Benefit from Specialist Intervention? *Journal of Banking and Finance* vol 27, no 9. September, 1823-54.

Pagano M. and A. Roell, 1992. Auction and Dealership Markets. What is the Difference? *European Economic Review*, 36, 613-623.

Patell, J. and M. Wolfson 1984. The Intraday Speed of Adjustment of Stock Prices to Earnings and Dividend Announcements *Journal of Financial Economics* 13, 223-252.

Stambaugh, R. 1999. Predictive Regressions *Journal of Financial Economics*, Vol. 54, 375-421.

Theissen 2002. Floor Versus Screen Trading: Evidence from the German Stock Market *Journal of Institutional and Theoretical Economics*, Vol 158, no1 March, 32-54.

Venkataraman, Kumar and Andrew C. Waisburd 2007. The Value of the Designated Market Maker *Journal of Financial and Quantitative Analysis*, Vol. 42. No. 3, Sept. 2007, 735-758.

Weill, Pierre-Olivier, 2009 Liquidity Provision in Capacity Constrained Markets *working paper* March http://www.econ.ucla.edu/poweill/capacity.pdf

Appendix A:

NASDAQ – The National Association of Securities Dealers Automated Quote System was founded February 8, 1971 as the first electronic stock exchange in the world. It was created as a means to increase the trading of Over-the-Counter stocks, those that were unable to meet listing requirements for larger exchanges. On the first day of trading, the NASDAQ listed 2,500 OTC stocks. It was not until the 1990's that the NASDAQ began to be seen as a competitor of the NYSE. In 1994, for the first time, the NASDAQ beat the NYSE in annual shares traded. In 1998, the NASDAQ merged with the American Stock Exchange, which mostly traded options and derivatives, creating the NASDAQ-AMEX Market Group, for which they still operate as separate exchanges.

NYSE[11] – The New York Stock Exchange began with the Buttonwood Agreement in 1792. The NYSE was established as an outcry market, but in 2000 began to integrate an electronic exchange. On October 21, 2000 the NYSE set up Direct+, which was established as an automatic execution service. On January 24, 2002 the OpenBook system was launched which allowed off-floor market participants to view the buy and sell interest beyond the best bid and offer. August 2, 2004 the NYSE files to expand the Direct+ system, eliminating the size, time, and type of order requirements. December 15, 2005 the NYSE officially moved to a hybrid market, but it took until January 24, 2007 to integrate all stocks onto this market. The NYSE says that the percentage of volume executed on the automated exchange increased from 18.8% before the hybrid integration to 80% afterwards.

LSE – The London Stock Exchange began in 1698 as dealers made trades in the street and coffee houses and became an officially regulated exchange in 1801. The market was set up as an outcry market where people met to execute trades. The two large indexes on the LSE are the FTSE100 and FTSE250 (the FTSE is a joint venture with the Financial Times and the London Stock Exchange) where the FTSE100 is the largest, in terms of market capitalization, 100 firms, and the FTSE250 is the next 250 largest firms. On October 20, 1997 the Stock Exchange Trading System (SETS) was established, which is an electronic order book platform for the stocks in the FSTE100. Thus in 1997, the FSTE100 went from a quote-driven market to an order driven market. By September 1999 some of the stocks on the FTE-250 were added to the system (Lai 2007), and on November 3, 2003, the SETSmm was launched. The SETSmm is a system that uses the electronic order book system with the market makers to establish a hybrid market for all stocks in the FSTE250 that are not being traded on the SETS system. On October 29, 2007 the LSE officially went to a hybrid system for these indexes.

[11] The NYSE also has an 'upstairs market' to match large orders. This still exists, but not all large orders are taken upstairs. Many of these orders are broken up and processed through the trading floor to increase anonymity.

Appendix B

Second Robustness Check, matching NYSE and NASDAQ stocks that have matching 2-digit SIC codes and market capitalization

Financial

	NASDAQ	NYSE	SIC Code
1	HBAN	CMA	60
2	NTRS	BBT	60
3	TROW	BEN	62
4	CINF	TMK	63
5	FITB	STI	67

Information Technology

	NYSE	NASDAQ	SIC Code
1	MU	AMAT	35
2	XRX	JAVA	35
3	EMC	DELL	35
4	HPQ	AAPL	35
5	AMD	MOLX	36
6	NSM	XLNX	36
7	ADI	TLAB	36
8	MOT	QCOM	36
9	TXN	CSCO	36
10	TER	KLA	38
11	CSC	ADBE	73
12	ADP	YHOO	73

.

Figures:

Figure I: Monthly standard deviation, six months before and after each switch to a quasi-hybrid or hybrid system, relative to the NASDAQ standard deviation.

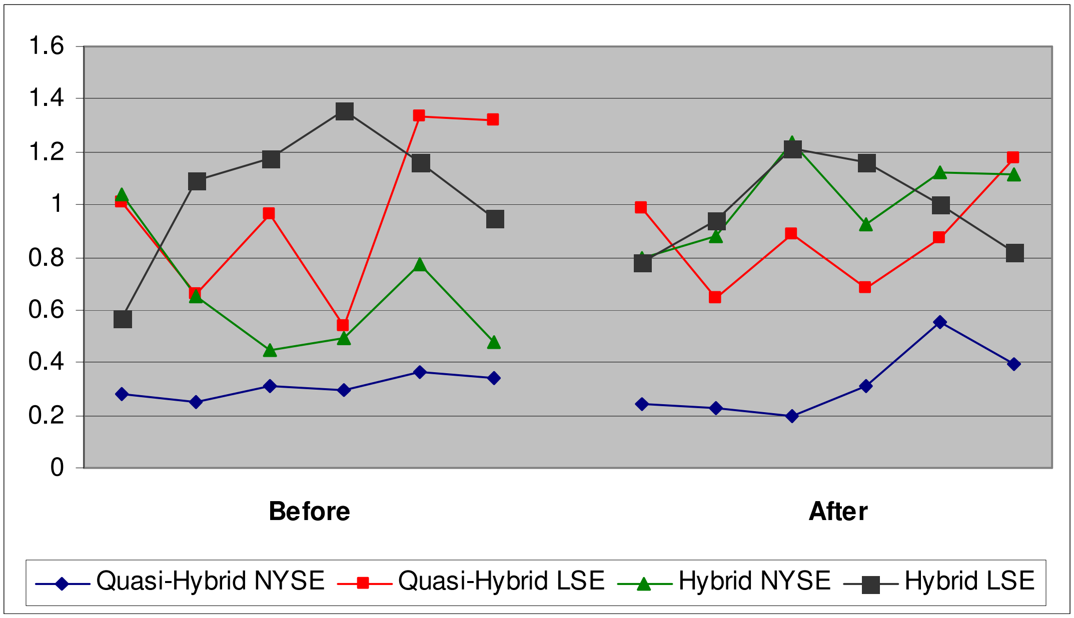


Figure II: Yearly standard deviation of the NYSE and NASDAQ.

This figure shows how the yearly variation changes over time. It compares the NYSE with the NASDAQ and shows the quasi-hybrid (dotted line) and hybrid (solid line) market switches. I use December 2006 as the switch to a Hybrid market following Hendershott and Moulton (2009).

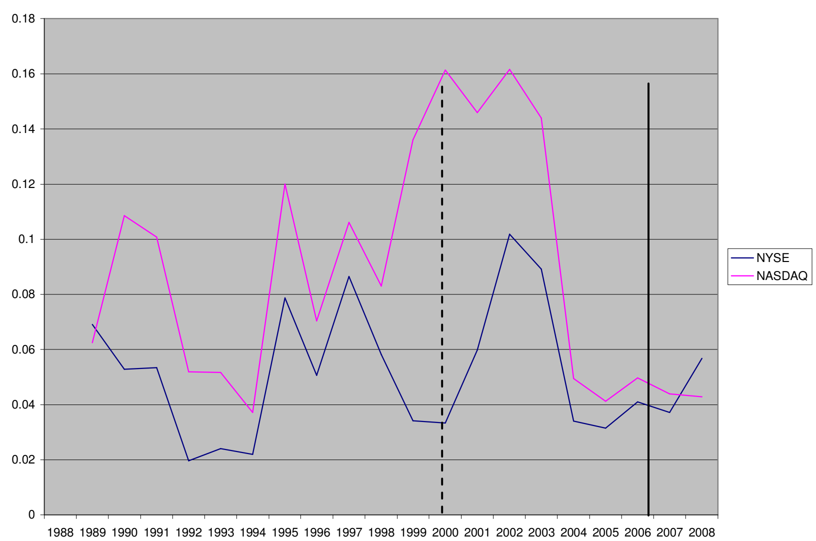


Figure III: Yearly standard deviation of the FTSE100 and NASDAQ
This figure shows how the yearly variation changes over time. It compares the FTSE100 with the NASDAQ and shows the quasi-hybrid (dotted line) and hybrid (solid line) market switches.

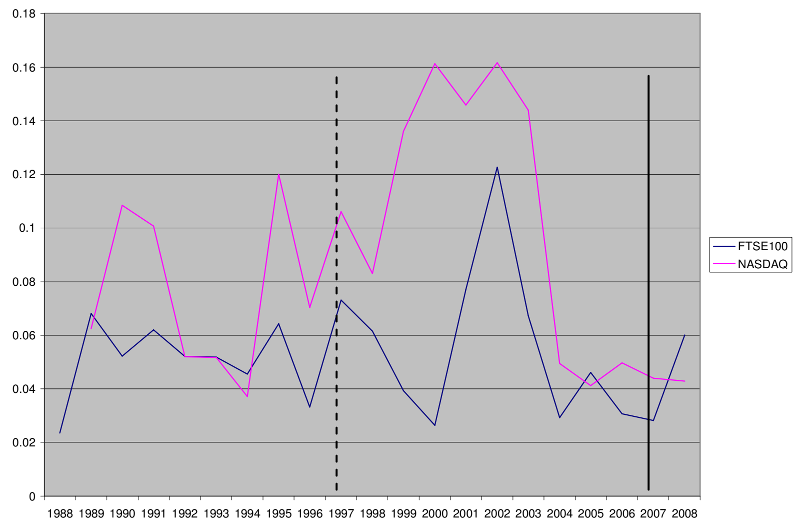
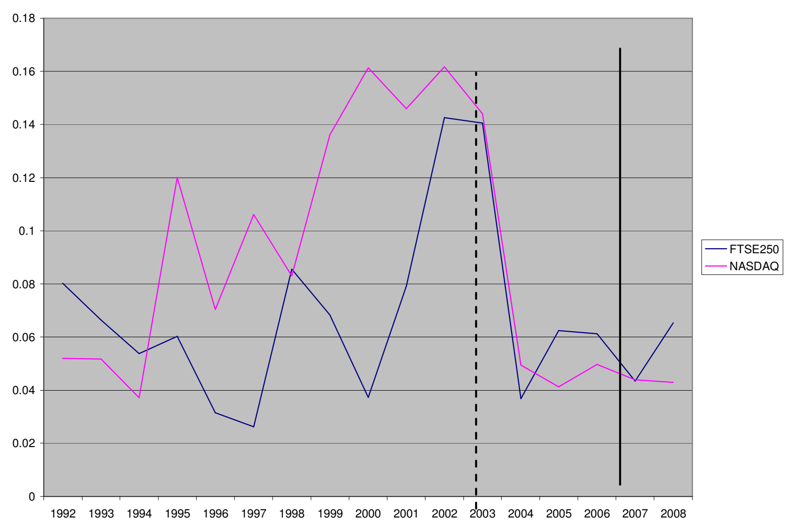


Figure IV: Yearly standard deviation of the FTSE250 and NASDAQ
This figure shows how the yearly variation changes over time. It compares the FTSE250 with the NASDAQ and shows the quasi-hybrid (dotted line) and hybrid (solid line) market switches.



Tables:

Table I: By trading platform, the number of times per month that there was at least a 2% one day change.

		NASDAQ		NYSE
Auction			Apr 1986-Oct 2000	1.0114
Quasi-Hybrid			Oct 2000-Dec 2006	1.4942
Hybrid			Dec 2006-Feb 2009	5.3804
Electronic	Apr 1986-Feb 2009	3.8695		
		FTSE100		FTSE250
Auction	Apr 1986-Oct 1997	0.7705	Apr 1986-Sept 1999	0.5934
Quasi-Hybrid	Oct 1997-Oct 2007	2.5721	Sept 1999-Oct 2007	1.0000
Hybrid	Oct 2007-Feb 2009	7.1006	Oct 2007-Sept 2008	7.8106
Electronic				

Table II: Standard Deviation by market for each year.

Year	NYSE	NASDAQ	FTSE100	FTSE250
1991	0.053379	0.100616	0.062035	
1992	0.019629	0.051919	0.052076	0.0801886
1993	0.024074	0.051679	0.051814	0.0664208
1994	0.021961	0.037098	0.045567	0.0537295
1995	0.078726	0.120116	0.064254	0.0601936
1996	0.050724	0.070422	0.033314	0.031442
1997	0.08646	0.106063	0.073116	0.0262905
1998	0.058261	0.080331	0.06152	0.0855543
1999	0.034211	0.13603	0.039325	0.0683148
2000	0.033397	0.161091	0.026489	0.037216
2001	0.05984	0.146096	0.077018	0.0791659
2002	0.101848	0.161468	0.122678	0.1424859
2003	0.089191	0.143982	0.067238	0.1405881
2004	0.034081	0.049376	0.029236	0.0368388
2005	0.031459	0.041137	0.046221	0.0624901
2006	0.040987	0.049662	0.030757	0.0611481
2007	0.037188	0.043923	0.028283	0.0434609
2008	0.198807	0.177708	0.143135	0.1925885
2009	0.092173	0.064136	0.071606	0.0452739

Table III: Variance ratio test for each market, relative to the NASDAQ, for each year. An * indicates when equation 10 has a p-value not equal to 1 (so the statistical probability of the ratio being greater than 1 is not 100%). The bold numbers represent the years that the given market switched to a quasi-hybrid or hybrid market.

Year	NYSE / NASDAQ		FTSE100 / NASDAQ		FTSE250 / NASDAQ	
1991	0.530525		0.616551			
1992	0.378069		1.003036	*	1.544509	*
1993	0.465837		1.002618	*	1.285267	*
1994	0.591973		1.228279	*	1.448313	*
1995	0.655413		0.534934		0.501127	
1996	0.720281		0.473059		0.446479	
1997	0.815177		**0.689368**		0.247877	
1998	0.725267		0.765834		1.065022	*
1999	0.251493		0.28909		0.502203	
2000	**0.207318**		0.164433		0.231025	
2001	0.409592		0.527173		0.541877	
2002	0.630762		0.75977		0.882441	*
2003	0.61946		0.466993		**0.976431**	*
2004	0.69023		0.592115		0.746092	
2005	0.764745		1.123589	*	1.519073	*
2006	**0.825316**		0.619324	*	1.231293	*
2007	0.84668	*	**0.643919**		**0.989488**	*
2008	1.118727	*	0.80545		1.083736	*
2009	1.437156	*	1.116477	*	0.70591	*

* Variance ratio test has the H_a: Ratio > 1 <u>not</u> equal to 100%

Table IV: RDID test for NYSE/NASDAQ.

150 Days	NYSE	NASDAQ	RDiD
Before Quasi-Hybrid	0.020641	0.058889	0.786436
After Quasi-Hybrid	0.017836	0.064704	
Before Hybrid	0.013679	0.01856	1.352217
After Hybrid	0.014078	0.014126	

300 Days	NYSE	NASDAQ	RDiD
Before Quasi-Hybrid	0.019812	0.048487	0.905672
After Quasi-Hybrid	0.021382	0.057779	
Before Hybrid	0.013006	0.016576	1.216611
After Hybrid	0.019429	0.020354	

450 Days	NYSE	NASDAQ	RDiD
Before Quasi-Hybrid	0.018865	0.043234	0.908941
After Quasi-Hybrid	0.019796	0.049912	
Before Hybrid	0.012352	0.016255	1.201815
After Hybrid	0.019759	0.021636	

Table V: RDID test for FTSE100/NASDAQ.

150 Days	FTSE100	NASDAQ	RDID
Before Quasi-Hybrid	0.020056	0.024133	1.16174
After Quasi-Hybrid	0.021754	0.022531	
Before Hybrid	0.016985	0.017301	1.019783
After Hybrid	0.026537	0.026506	

300 Days	FTSE100	NASDAQ	RDID
Before Quasi-Hybrid	0.016254	0.021348	1.010708
After Quasi-Hybrid	0.025432	0.03305	
Before Hybrid	0.014958	0.015924	0.976508
After Hybrid	0.034127	0.037205	

450 Days	FTSE100	NASDAQ	RDID
Before Quasi-Hybrid	0.014447	0.022087	1.106322
After Quasi-Hybrid	0.023996	0.033161	
Before Hybrid	0.014816	0.016454	1.033082
After Hybrid	0.03472	0.037323	

Table VI: RDID test for FTSE250/NASDAQ.

150 Days	FTSE250	NASDAQ	RDID
Before Quasi-Hybrid	0.019422	0.031496	0.831707
After Quasi-Hybrid	0.022641	0.044145	
Before Hybrid	0.016985	0.017301	1.019783
After Hybrid	0.026537	0.026506	

300 Days	FTSE250	NASDAQ	RDID
Before Quasi-Hybrid	0.025947	0.040018	0.645843
After Quasi-Hybrid	0.021277	0.050809	
Before Hybrid	0.014958	0.015924	0.976508
After Hybrid	0.034127	0.037205	

450 Days	FTSE250	NASDAQ	RDID
Before Quasi-Hybrid	0.023729	0.034336	0.529905
After Quasi-Hybrid	0.020771	0.056718	
Before Hybrid	0.014816	0.016454	1.033082
After Hybrid	0.03472	0.037323	

Table VII: Summary Statistics for each market. Using monthly standard deviation data for equation 5 (σ: $X_t = \beta_0 + \beta_1\ \sigma$: $NASDAQ_t + \beta_2\ (Electronic_t) + \varepsilon$).

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	218	1999.587	5.255168	1991	2009
NYSE	218	0.016274	0.011507	0.0041899	0.100158
NASDAQ	218	0.025208	0.016317	0.0064531	0.087822
Quasi-hybrid	217	0.46083	0.499616	0	1
Hybrid	217	0.119816	0.325497	0	1

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	218	1999.587	5.255168	1991	2009
FTSE100	218	0.017949	0.011272	0.0057577	0.08474
NASDAQ	218	0.025208	0.016317	0.0064531	0.087822
Quasi-hybrid	217	0.626728	0.484792	0	1
Hybrid	217	0.073733	0.26194	0	1

Table VIII: Event study results.

	NYSE	NYSE	FTSE100	FTSE100
NASDAQ	0.465	0.470	0.378	0.354
	(13.10)**	(14.58)**	(9.09)**	(9.47)**
Quasi-hybrid	0.003		0	
	(2.51)*		(0.17)	
Hybrid		0.011		0.012
		(6.90)**		(5.33)**
Constant	0.003	0.003	0.008	0.008
	(2.86)**	(3.15)*	(6.46)**	(7.33)**
Seasonal Effects	No	No	No	No
Observations	217	217	217	217
R-squared	0.47	0.55	0.31	0.39

Absolute value of t-statistics in parentheses
* significant at 5%; ** significant at 1%

Table IX: Event study results with monthly controls.

	NYSE	NYSE	FTSE100	FTSE100
NASDAQ	0.461	0.465	0.375	0.346
	(12.73)**	(14.16)**	(9.01)**	(9.38)**
Quasi-hybrid	0.003		0	
	(2.50)*		(0.23)	
Hybrid		0.011		0.013
		(6.85)**		(5.68)**
Constant	0.002	0.003	0.014	0.006
	(0.82)	-1.5	(5.84)**	(2.86)**
Seasonal Effects	Yes	Yes	Yes	Yes
Observations	217	217	217	217
R-squared	0.49	0.57	0.36	0.45

Absolute value of t-statistics in parentheses
* significant at 5%; ** significant at 1%

Table X: GARCH RDID test for NYSE/NASDAQ.

150 Days	OPG Std. Err.		
	NYSE	NASDAQ	RDiD
Before Quasi-Hybrid	0.028158	0.019235	2.071935
After Quasi-Hybrid	0.035732	0.011781	
Before Hybrid	0.014435	0.014381	1.089749
After Hybrid	0.01684	0.015395	

300 Days	NYSE	NASDAQ	RDiD
Before Quasi-Hybrid	0.01853	0.005513	0.062263
After Quasi-Hybrid	0.011559	0.055237	
Before Hybrid	0.007847	0.009846	1.52604
After Hybrid	0.014488	0.011913	

450 Days	NYSE	NASDAQ	RDiD
Before Quasi-Hybrid	0.012551	0.003519	0.505609
After Quasi-Hybrid	0.007614	0.004223	
Before Hybrid	0.004539	0.006371	1.314732
After Hybrid	0.008387	0.008953	

Table XI: GARCH RDID test for FTSE100/NASDAQ.

150 Days	Std. Err.		
	FTSE100	NASDAQ	RDID
Before Quasi-Hybrid	0.013511	0.006192	0.575023
After Quasi-Hybrid	0.014878	0.011857	
Before Hybrid	0.041439	0.024045	0.861851
After Hybrid	0.027014	0.018187	

300 Days	FTSE100	NASDAQ	RDID
Before Quasi-Hybrid	0.005079	0.004579	1.421455
After Quasi-Hybrid	0.011971	0.007592	
Before Hybrid	0.014323	0.008554	0.579763
After Hybrid	0.008779	0.009043	

450 Days	FTSE100	NASDAQ	RDID
Before Quasi-Hybrid	0.003191	0.002987	2.259176
After Quasi-Hybrid	0.008091	0.003353	
Before Hybrid	0.008527	0.005044	0.614358
After Hybrid	0.005315	0.005118	

Table XII: Rolling window robustness test for NYSE.

151-300	NYSE	NASDAQ	RDiD
Before Quasi-Hybrid	0.018953	0.039583	0.989523
After Quasi-Hybrid	0.022686	0.04788	
Before Hybrid	0.011114	0.013476	1.082436
After Hybrid	0.023123	0.025901	

301-450	NYSE	NASDAQ	RDiD
Before Quasi-Hybrid	0.016998	0.032685	0.944328
After Quasi-Hybrid	0.015627	0.03182	
Before Hybrid	0.010445	0.015305	1.193262
After Hybrid	0.019936	0.024481	

Table XIII: Rolling window robustness test for FTSE100.

Days 151-300	FTSE100	NASDAQ	RDID
Before Quasi-Hybrid	0.012775	0.017773	0.934827
After Quasi-Hybrid	0.031469	0.046831	
Before Hybrid	0.012922	0.014524	0.94562
After Hybrid	0.043899	0.052179	

Days 301-450	FTSE100	NASDAQ	RDID
Before Quasi-Hybrid	0.017072	0.023437	0.871184
After Quasi-Hybrid	0.020075	0.031635	
Before Hybrid	0.015771	0.017199	1.148621
After Hybrid	0.04073	0.038669	

Table XIV: GARCH robustness test for NYSE.

151-300	NYSE	NASDAQ	RDiD
Before Quasi-Hybrid	0.025745	0.008322	0.372638
After Quasi-Hybrid	0.019613	0.017013	
Before Hybrid	0.011666	0.015174	1.777686
After Hybrid	0.024701	0.018073	

301-450	NYSE	NASDAQ	RDiD
Before Quasi-Hybrid	0.023957	0.019441	1.21876
After Quasi-Hybrid	0.036969	0.024614	
Before Hybrid	0.018957	0.015237	0.48108
After Hybrid	0.019719	0.032946	

Table XV: GARCH robustness test for FTSE100.

Days 151-300	FTSE100	NASDAQ	RDID
Before Quasi-Hybrid	0.014768	0.014051	1.275913
After Quasi-Hybrid	0.021807	0.016261	
Before Hybrid	0.025844	0.016806	0.078847
After Hybrid	0.014708	0.121299	

Days 301-450	FTSE100	NASDAQ	RDID
Before Quasi-Hybrid	0.040773	0.01299	0.37049
After Quasi-Hybrid	0.027594	0.023729	
Before Hybrid	0.033092	0.015548	0.326657
After Hybrid	0.043871	0.063101	

Table XVI: Robustness test with Finance matching stocks.

Finance			
150 Days			RDiD
	NYSE	NASDAQ	
Before Quasi-Hybrid	0.057193	0.069867	1.153776
After Quasi-Hybrid	0.052155	0.055222	
Before Hybrid	0.023313	0.039188	1.692409
After Hybrid	0.024866	0.024698	
300 Days			RDiD
	NYSE	NASDAQ	
Before Quasi-Hybrid	0.070526	0.08007	1.012525
After Quasi-Hybrid	0.046059	0.051645	
Before Hybrid	0.023241	0.035224	1.39643
After Hybrid	0.039724	0.043115	
450 Days			RDiD
	NYSE	NASDAQ	
Before Quasi-Hybrid	0.062106	0.067018	0.909013
After Quasi-Hybrid	0.040986	0.048655	
Before Hybrid	0.024074	0.032883	1.201028
After Hybrid	0.052455	0.059657	

Table XVII: Robustness test with Information Technology matching stocks.

Information Technology

150 Days			RDiD
	NYSE	NASDAQ	
Before Quasi-Hybrid	0.145905	0.104174	0.580919
After Quasi-Hybrid	0.119421	0.146777	
Before Hybrid	0.049616	0.060355	1.259168
After Hybrid	0.039137	0.03781	

300 Days			RDiD
	NYSE	NASDAQ	
Before Quasi-Hybrid	0.129817	0.131389	0.914103
After Quasi-Hybrid	0.115651	0.12805	
Before Hybrid	0.046403	0.055698	1.156673
After Hybrid	0.055506	0.0576	

450 Days			RDiD
	NYSE	NASDAQ	
Before Quasi-Hybrid	0.11881	0.126478	0.966603
After Quasi-Hybrid	0.105028	0.115669	
Before Hybrid	0.046448	0.053981	1.112042
After Hybrid	0.056645	0.0592	