How Market Makers Affect Efficiency: Evidence that Markets are Becoming Less Efficient

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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 informational 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 with increasing adoption of the hybrid market, there is increasing market volatility (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.

Keywords: Hybrid market, information efficiency, market efficiency, speed efficiency
JEL classification: G12, G14, G15

1. Introduction

Electronic markets are being increasingly used in a majority of equity and derivative markets around the world. Two of the world's major exchanges, the New York Stock Exchange (NYSE) and the London Stock Exchange (LSE), have 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. Although the speed has increased, this does not necessarily mean that informational efficiency has increased.

Market makers, formally known as specialists or designated market makers on the NYSE, have long been involved in the trading process. Because different exchanges use different titles, in this work I use the term 'market maker' in the most general sense. The term market maker is used for a person who is designated to make market transactions work more efficiently and provide liquidity. The analysis of their involvement of the trading process is vital as technology increases the speed of transactions. As exchanges have moved to this hybrid system, the market makers' role has changed. This change has increased the transaction speed. Hendershott and Moulton (2011) find that the net effect of this action is positive; however, this study focuses on informational efficiency as the market makers lose their ability to provide liquidity in the market.

Although it is possible that the hybrid market could result in an increase in price discovery, in the past market makers would provide bid/ask spreads as the random arrivals of orders were processed. With the integration of the hybrid markets the market makers 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 mitigates the market makers' ability to stabilise prices. I expand the research to informational efficiency

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by analysing the relative volatility as a measure of informational efficiency. Following Gulen and Mayhew (2000), I use market index funds to measure changes in volatility and the impact on informational efficiency.

Before the hybrid system, as large continuous orders came in, market makers had the ability to match these 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. Thus these large continuous orders can no longer be matched by market makers, decreasing their ability to stabilise prices. The main contribution of this paper is the analysis of changes in informational efficiency as technology has increased the speed of transactions.

I test if there is a loss in informational efficiency by examining the changes in volatility over time as the NYSE and LSE move from an auction system to a hybrid format. Four tests are used: an event study, rolling window test, GARCH estimation, and matching data. Section 2 discusses the implications of having market makers in the transaction process followed by Section 3 which gives a brief background of the market systems. Section 4 discusses the methodology and Section 5 explains the data and results. Section 6 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 helps stabilise prices. Gromb and Vayanos (2002) and Weill (2011) 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), 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 been extended to electronic markets and their use of market makers (Bessembinder *et al.* 2007) and specialists as risk managers (Mao and Pagano 2007).

A common argument in support of electronic markets is that the electronic aspect increases liquidity. Chordia *et al* (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 this 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 of these large continuous orders, previously brought by the market makers, is no longer present, meaning informational efficiency is decreasing despite the increase in speed efficiency.

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 synchronised. This paper looks at the ability of market makers to alleviate the synchronisation problem. Market makers have the ability to combine large, consistent, buy (sell) orders with matching sell (buy) orders. However, with the introduction of the hybrid system, their ability to so in between the best bid and ask 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 aim to examine the changes in volatility over time by comparing the NYSE and LSE as they move from auction systems to hybrid systems.

3. Background

In the last decade, stock markets around the world have been initialising 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 per cent decline in the number of traders on the floor.[1]

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 Programme (September 2006):[2]

> "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 is designed to allow for more flexibility and faster trades.

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 (LRPs). The LRPs were created to "help curb wide price movements resulting from automatic executions and sweeps over a short period of time."[3] The NYSE also established an Application Programming Interface (API) that allows market makers to connect with specialist firms through the NYSE's electronic 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.

As the NYSE and LSE have become increasingly electronic, others have been, and remain, electronic throughout the sample. In 1971 the National Association of Securities Dealers (NASD) made an electronic quotation system called NASDAQ available to dealers and brokers.[4] The National Association of Securities Dealers Automated Quote System

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

2 *http://www.nyse.com/pdfs/hm_booklet.pdf*

3 Also from the NYSE Hybrid Training Programme, September 2006.

4 The NASDAQ system was a telephone market until the late 1980s, and therefore it was electronic over the sample period studied. The first electronic exchange was the Toronto Stock Exchange which started the Computer Assisted Trading System(CATS) in 1977.

(NASDAQ) was set up as an online trading platform, for which orders can be made, and processed, electronically. It is widely believed that an electronic market is more volatile than a dealership, or auction market (Pagano and Roell 1992; Madhavan and Smidt 1991; Theissen 2002).

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 (Galariotis and Giouvris 2007). However, not all markets are going through this transition. Because the NASDAQ used electronic trading throughout this sample, 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 of NASDAQ, NYSE and LSE, can be found in Appendix A.

4. Methodology

To look at informational 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 Stock Electronic Trading Service (SETS) system, which Galariotis and Giouvris (2007) call 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 moved to a hybrid system. These markets were changing regimes at different points in time, and it is therefore testable to see how these markets responded to the changes in the trading regime. The FTSE 100 went to a quasi-hybrid system in October 1997 and a hybrid system in October 2007. The NYSE went to a quasi-hybrid system in October 2000 and a hybrid system in December 2006.

It is commonly thought that 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 whether 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).[5]

A simple example explains the concept effectively: There are many traders, assume we have two with very large orders for the same stock.[6] Institution B is a net buyer of a given stock and Institution S is a net seller of that same stock. Both institutions are making trades

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5 This is not refuting the findings of Hendershott and Moulton (2011), rather providing more details about the information efficiency.

6 It is possible for these orders to be taken to the upstairs market, but this is 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.

large enough to move the price, so they choose to make their trades in smaller lots over a period, so as not to influence the price. If both of these institutions are trying to execute orders over the same period, matching these orders can be valuable and can decrease volatility in the stock. As the markets began to run on a hybrid system, the ability of market makers to match these orders 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) states, "trading takes place over a trading day, which begins at time $t = 0$ and ends at time $t = 1$." Although the market clears by assumption in this model, it is the matching of each individual order that I focus on. 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 trade 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 reveals the value of a market maker.[7] 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.

There are four different tests to verify the hypothesis that the electronic markets increase volatility and thus decrease informational efficiency.

a. Event Study
b. Rolling Window Test
c. GARCH
d. Data Matching

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:

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

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. I also use a relative difference-in-difference (RDID) measure (Equation 3) for the rolling window and GARCH test.

Although the DID setup tests the difference through subtraction, this RDID measure will use a percentage change for a more accurate evaluation.

4.1 *Event Study*

I create a data set of monthly standard deviations for each index. With these 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 form of electronic trading system.

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[7] 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.

$$\sigma{:}\, X_t = \beta_0 + \beta_1\, \sigma{:}\, NASDAQ_t + \beta_2\,(Electronic_t) + \varepsilon \qquad (2)$$

Equation 2 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.

4.2 Rolling Window Test

To confirm the results found in the event study, I use a rolling window estimation of the variances before and after the event to measure the average variance over that time period. This allows for an accurate variance measurement before and after the regime switch. I look at the variance for days 1-25, then again for days 2-26, 3-27, and so on. The variance used is the average measure found for each 25-day window throughout any given period for each regime. Comparing the time periods before and after reveals the impact of this regime change. Because variance increases over time in a stochastic process, measuring the 50,[8] 150, 300, or 450 trading days before and after the switch provides the needed information for this test.[9] This rolling window setup allows the use of an average variance for each 25-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 25-day windows is then compared before and after each regime switch as an RDID:

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

where $\sigma{:}\, X_B$ is the standard deviation on the NYSE or FTSE100 before (B) the regime switch and $\sigma : NASDAQ_B$ is the standard deviation on the NASDAQ before X had a regime switch. $\sigma{:}\, X_A$ is the measure of the switching regime's standard deviation after (A) the switch, with $\sigma : NASDAQ_A$ 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.

$$\sigma : X_B \big/ \sigma : NASDAQ_B \qquad (4)$$

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

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8 For the 50-day test, the window used is 10 days, instead of 25.

9 These day ranges involve oversampling issues; however tests for oversampling problems reveal no issues.

time, 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 that 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.

4.3 GARCH

As is standard in time series variance measurement (Engle 2001), I also use the Generalized Autoregressive Conditional Heteroskedastic (GARCH) 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 generalised 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 financial data to be analysed more accurately through conditional variance modeling. Instead of worrying about the existence of heteroskedasticity, I use a GARCH estimation model:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}{}^2 + \beta_1 \sigma_{t-1}{}^2 \tag{5}$$

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 Nelson and Foster (1995) point 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 rolling 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 is not 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.

4.4 Data Matching

It is also important to note that because I am comparing different stock markets, the NASDAQ, in general, has different stocks trading than the other markets. As stated in Amihud and Mendelson (1987: 534) "the difficulty with empirical comparisons 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, I 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 these 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 construct a matched sample of companies in the S&P 500 index. I 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 capitalisations, and (c) have similar productions (according to their Standard Industrial Classification(SIC) Codes).

In these data, I include all stocks that have consistently been in the S&P500 from 2002 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 capitalisation, with each pair having a representative from each exchange.

Using 5 Finance matches and 12 IT matches, independently, I will average them and use Equation 6 to check if these two industries, and the markets they are traded on, are driving the results. This tests if the tech bubble, the financial crisis, or the exchanges, trading different equities, are driving the results found in the above tests.

$$\frac{\sigma : NYSE_{A;\,i,\,j} \big/ \sigma : NASDAQ_{A;\,i,\,j}}{\sigma : NYSE_{B;\,i,\,j} \big/ \sigma : NASDAQ_{B;\,i,\,j}} \qquad (6)$$

In Equation 6, $\sigma : NYSE$ is the average standard deviation of the stocks in the Finance (i) and Information Technology (j) sectors traded at the NYSE and $\sigma : NASDAQ$ 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 6 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 terms of variation to the all electronic market. Given Equation 6 is greater than one, it supports the hypothesis that 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, and the FTSE100 index. 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). 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. Utilised 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.

5.1 Event Study

This data uses the monthly standard deviations for each of the exchanges. Using a dummy variable for the type of market, whether it is a quasi-hybrid or hybrid market, I test the impact of a market change on the volatility of an index.

$$\sigma: X_t = \beta_0 + \beta_1\, \sigma: NASDAQ_t + \beta_2\, (Electronic_t) + \varepsilon \qquad (2)$$

Equation 2 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 1.

Table 2 shows the regressions for the event study, on the quasi-hybrid and hybrid systems with no controls for seasonal effects. Table 3 shows the same regression but includes monthly dummy variables, as fixed effects, to control for seasonal differences in variation.[10] 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.[11] However the regression on the quasi-hybrid system is only significant for the NYSE, not the FTSE100. On the whole these results support the hypothesis that volatility is increasing as markets move to an electronic system.

5.2 Rolling Window Test

For the rolling window variance test, a 25-day window is used. This means that for the time period in the study, standard deviations are estimated for the first 25 days, then on days 2-26, 3-27 and so on. Therefore, the standard deviation reported is the average standard

Table 1. Summary statistics for each market. Monthly standard deviation data are used for Equation 2 ($\sigma: X_t = \beta_0 + \beta_1 \sigma: NASDAQ_t + \beta_2 (Electronic_t) + \varepsilon$).

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

[10] 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.

[11] 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.

Table 2. 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%
Note: The results from Equation 2, the event study. The dummy variable *Quasi-Hybrid* or *Hybrid*, given they are positive and significant, support the hypothesis that volatility is increasing in that market after the switch and shows support for the hypothesis that markets are becoming less efficient.

Table 3. 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%
Note: The results from Equation 2, the event study, with monthly controls for seasonal volatility effects. The dummy variable *Quasi-Hybrid* or *Hybrid*, given they are positive and significant, support the hypothesis that volatility is increasing in that market after the switch and shows support for the hypothesis that markets are becoming less efficient.

deviation for all 25-day windows in each time period. The time periods used are 50 days,[12] 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:

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

Recall that when Equation 3 is greater than one when the regime switch causes the variation to increase relative to the NASDAQ market. In Tables 4 and 5 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.

The NYSE had a significant impact on the move to a hybrid market, but not from the quasi-hybrid market. The FTSE100 has strong results showing the move to a quasi-hybrid market has a significant impact of volatility; however the move to a hybrid market gives mixed results. 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.

5.3 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)[13] 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.

Using the GARCH approach for the NYSE (Table 6), 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 decreases 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.

The estimation using a GARCH approach with the FTSE100 (Table 7) gives mixed results for the move to the quasi-hybrid market and refutes the theory for the hybrid market.

5.4 Data Matching

Matching stocks that have been on the S&P500 consecutively by SIC Code and market capitalisation produce the following results.

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12 The window used for the 50 day test is 10 days, rather than 25 which is used for the 150-, 300- and 450-day tests.

13 The standard errors can be used in this case because the number of observations is equal in all regressions.

Table 4. RDID test for NYSE/NASDAQ

50 Days	NYSE	NASDAQ	RDID
Before Quasi-Hybrid	0.009558	0.026859	0.943866
After Quasi-Hybrid	0.011636	0.034644	
Before Hybrid	0.006638	0.010569	1.948054
After Hybrid	0.011836	0.009675	
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	

Note: Table 4 measures the Standard Deviation of the NYSE and the NASDAQ before and after the changes to the quasi-hybrid and hybrid markets. The relative difference-in-difference (RDID) is a measure for the effects of the changing market. A RDID greater than one supports the theory that volatility is increasing and the markets are becoming less efficient.

Table 5. RDID test for FTSE100/NASDAQ

50 Days	FTSE100	NASDAQ	RDID
Before Quasi-Hybrid	0.015146	0.018668	1.240816
After Quasi-Hybrid	0.019883	0.01975	
Before Hybrid	0.013633	0.012422	0.847295
After Hybrid	0.017735	0.019073	
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	

Note: Table 5 measures the Standard Deviation of the FTSE100 and the NASDAQ before and after the changes to the quasi-hybrid and hybrid markets. The relative difference-in-difference (RDID) is a measure for the effects of the changing market. A RDID greater than one supports the theory that volatility is increasing and the markets are becoming less efficient.

Table 6. 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	

Note: Table 6 measures the GARCH Standard Errors of the NYSE and the NASDAQ before and after the changes to the quasi-hybrid and hybrid markets. The relative difference-in-difference (RDID) is a measure for the effects of the changing market. A RDID greater than one supports the theory that volatility is increasing and the markets are becoming less efficient.

Table 7. 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	

Note: Table 7 measures the GARCH Standard Errors of the FTSE100 and the NASDAQ before and after the changes to the quasi-hybrid and hybrid markets. The relative difference-in-difference (RDID) is a measure for the effects of the changing market. A RDID greater than one supports the theory that volatility is increasing and the markets are becoming less efficient.

As you can see in Tables 8 and 9, the results are supported by the Financial stocks and split for the IT stocks. This test supports the hybrid market having an impact, but gives mixed results for the regime switch to a quasi-hybrid market.

6. Conclusion

The informational efficiency of markets, equity and future markets alike, matter to the transactions made there. This study uses the volatility of market exchanges to analyse the effects of moving to a hybrid system. There have been two main impacts of markets, like the NYSE and LSE, moving to an electronic trading platform that have ultimately led to a

Table 8. Finance matching stocks

	Finance		
150 Days	NYSE	NASDAQ	RDID
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	NYSE	NASDAQ	RDID
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	NYSE	NASDAQ	RDID
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	

Note: Table XVI is matched data of finance stocks. Stocks are matched if they are in the S&P 500 continuously from 2000-2009 and have a match with a similar market capitalisation. This is measuring the Standard Deviation of the NYSE and the NASDAQ before and after the changes to the quasi-hybrid and hybrid markets. The relative difference-in-difference (RDID) is a measure for the effects of the changing market. A RDID greater than one supports the theory that volatility is increasing and the markets are becoming less efficient.

Table 9. Information Technology matching stocks

	Information Technology		
150 Days	NYSE	NASDAQ	RDiD
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	NYSE	NASDAQ	RDiD
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	NYSE	NASDAQ	RDiD
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	

Note: Table XVII is matched data of information technology stocks. Stocks are matched if they are in the S&P 500 continuously from 2000-2009 and have a match with a similar market capitalisation. This is measuring the Standard Deviation of the NYSE and the NASDAQ before and after the changes to the quasi-hybrid and hybrid markets. The relative difference-in-difference (RDID) is a measure for the effects of the changing market. A RDID greater than one supports the theory that volatility is increasing and the markets are becoming less efficient.

decrease in information contained in the price at a given point in time. The first has been an increase in trading speed, which at first was thought to increase efficiency. However, it is important to separate the speed efficiency from informational efficiency. Although trades can be conducted more quickly, there can simultaneously be a decrease in informational efficiency. As trading speed increases 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.

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 analyse the effects of changing a market from an auction system to an electronic system, by utilising the dates in which a quasi-hybrid or hybrid market was adopted. Using a RDID (relative difference-in-difference) approach, comparing the NYSE and LSE to an all electronic market (NASDAQ), measures the convergence of the 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 informational efficiency (Table 10).

Table 10. The results from each of the four tests (Event Study, Rolling Window Test, GARCH, and Matching Data) for both the NYSE index and FTSE 100

Test	Results			
	NYSE		FTSE100	
	Auction to Quasi-Hybrid	Quasi-Hybrid to Hybrid	Auction to Quasi-Hybrid	Quasi-Hybrid to Hybrid
a. Event Study	Supports	Supports	Neither	Supports
b. Rolling Window Test	Refutes	Supports	Supports	Neither
c. GARCH	Neither	Supports	Neither	Refutes
d. 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 GARCH tests neither support nor refute the hypothesis. However, when using the rolling window RDID test and event study test, the hypothesis is supported. In addition to those tests, the matching data continues to show evidence that there is a decrease in informational efficiency. 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 continued debate.

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Appendix A

NASDAQ – The National Association of Securities Dealers Automated Quote System was founded 8 February 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 1990s 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[14] – 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 21 October 2000 the NYSE set up Direct+, which was established as an automatic execution service. On 24 January 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. On 2 August 2004, the NYSE filed to expand the Direct+ system, eliminating the size, time, and type of order requirements and on 15 December 2005, the NYSE officially moved to a hybrid market, but it took until 24 January 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 per cent before the hybrid integration to 80 per cent 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) whereas the FTSE100 is the largest, in terms of market capitalisation, 100 firms, and the FTSE250 is the next 250 largest firms. On 20 October 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 3 November 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 29 October 2007, the LSE officially adopted a hybrid system for these indexes.

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[14] 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 capitalisation

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