Speed of convergence to market efficiency: The role of ECNs

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Abstract
Chordia, Roll and Subrahmanyam (2005, CRS) estimate the speed of convergence to market efficiency based on short-horizon return predictability of the 150 largest NYSE firms. We extend CRS to a broad panel of NYSE stocks and are first examine the relation between electronic communication networks and the corresponding informational efficiency of prices. Overall, we confirm CRS's result that price adjustments to new information occur on average within five to fifteen minutes for large NYSE stocks. We further show that it takes about twenty minutes longer for smaller firms to incorporate information into prices. Most importantly, we demonstrate that the speed of convergence to market efficiency is significantly related to the type of trading platform where orders are executed, even after controlling for trading costs, volatility, informational effects, institutional trading activity, and firm characteristics. Our findings provide direct answers and insights to issues raised in a recent SEC concept release document. Our sample period is characterized by highly volatile market in the midst of the financial crisis.

Keywords: ECN, Market efficiency; NYSE, Arca
JEL codes: G10, G14

1. Introduction

Modern trading technology increasingly affects the way how orders are entered, routed, and executed. Competition from alternative electronic markets (i.e. electronic communication networks, hereafter ECNs), regional exchanges, and regulatory pressures are forcing traditional exchanges to react and adapt. As ECNs began competing for order flows from major U.S. exchanges, NASDAQ and NYSE acquired some of the emerging ECNs in order to remain competitive. NYSE Euronext, the world's largest cash equities market, now trades more than one-third of the world's cash equity volume and offers its clients alternate trading platforms with trading models from a fully electronic system to what NYSE Euronext describes as a "high tech/high touch" trading floor system. One of the most successful ECNs is Euronext's NYSE Arca (hereafter Arca), an all-electronic trading platform with distinct market structure and certain advantages over the traditional NYSE floor trading (e.g. deeper liquidity, after hours trading, increased transparency, and efficiency of execution). As of March 2007, Arca accounts for approximately one sixth of all the shares traded on the U.S. financial markets; for NYSE-listed securities, Arca accounts for over 10% of the shares traded, a rapid increase from less about 3% in 2004 (Stoll 2006). Given the increasing importance of ECNs as alternate trading platforms, our main objective is to provide empirical evidence on the informational efficiency of prices of NYSE stocks whose orders are also routed and executed through the Arca ECN platform.

Prior literature provides mixed theoretical predictions on the informational efficiency of prices on ECNs compared to traditional exchanges. On one hand, some researchers propose that all-electronic trading should improve the efficiency of stock prices. Stoll (2006) argues that ECNs not only reduce the cost of providing liquidity, but also increase the accuracy of price signals. Lower trading costs and higher volume improve liquidity, which allows rational traders (arbitrageurs) to keep stock prices closer to their equilibrium values. On the other hand, other researchers find that trading on ECNs has a greater permanent price impact, and therefore is more likely to carry informed trades than the traditional markets (Barclay et al., 2003; Huang, 2002). There is also evidence in the literature that periods with more information asymmetry are associated with higher short-horizon return predictability and that trading volume is most strongly associated with market efficiency (Chung and Hrazdil, 2010). Further, those who believe that markets are dominated by uninformed or noise traders argue that the low cost of trading and high turnover on ECNs will lead to excessive uninformed trading driving stock prices away from their fundamental values (Shleifer and Summers, 1990). A third possibility also exists, that the efficiency of information processing will be the same between orders executed through an ECN and orders executed through a traditional trading platform. If NYSE provides sufficient liquidity (as is most likely the case for large, actively traded stocks) enhancing arbitrageurs' ability to take advantage of any mispricing, then the additional liquidity obtained through the ECN should not have incremental effect on increasing market efficiency. Therefore, whether and to what extent ECNs impact the informational efficiency of prices is an empirical issue. In our study, we take an exploratory approach; we concentrate on the NYSE stocks and focus our attention on the impact the ECN trading platform has on the price efficiency of these stocks. We directly measure whether and to what extent order execution through different trading venues results in different speeds of convergence to market efficiency between the Arca and the NYSE trades.

The speed of convergence to market efficiency is of interest to not only market microstructure researchers, but also investors, listed firms, regulators, and competing stock exchanges. Studying the returns to financial assets and the process through which markets become efficient is fundamental to understanding how economies work in allocating goods and services (O'Hara, 1997). Examining how alternative trading platforms affect the price discovery process is an important step towards exploring the process through which markets become efficient. Stock exchanges are also interested in enhancing price discovery. As the CEO of NYSE Euronext points out, building investor confidence in the equity markets is important and stock exchanges "must enhance transparency, price discovery and accountability across the marketplace" (Niederauer, 2010). Furthermore, in a recent SEC concept release document, the commission asks questions such as: "Are there useful metrics for assessing the quality of price discovery in equity markets, such as how efficiently prices respond to new information?" and "What is the best approach for assessing whether the secondary markets are appropriately supporting the capital-raising function for companies of all sizes?" (Securities and Exchange Commission, 2010). Results of our study provide direct answers and additional insights for addressing issues raised in these questions. We demonstrate that the speed of convergence is a feasible measure to assess how efficiently prices respond to new information. Our findings are consistent with the theoretical framework that information about future returns is contained in past order flows (Subrahmanyam, 2008), and that it may take some time for prices to reflect fully the impact of new information (Hillmer and Yu, 1979; Chan et al., 1996). Our results confirm that trading volume has the strongest impact on improving the speed of convergence to market efficiency. Overall, our results show that the ECN platform can play a significant role in the price formation process by further enhancing the speed of price adjustment to new information.

2. Data and Methods of Analysis

2.1 The Speed of convergence to market efficiency

We collect trade and quote data from the NYSE TAQ database on the population of 2,041 stocks traded simultaneously on NYSE and Arca during the first six months of 2008. Following Chordia at el. (2005, hereafter CRS) and Chordia et al. (2008), we use a returns predictability model to measure empirically the degree of short-horizon market efficiency. We estimate for every stock on each of the two trading platforms the following returns predictability model:

$$Return_t = \alpha + \beta_1 OrderImbalance_{t-1} + \varepsilon_t \tag{1}$$

where $Return_t$ is the stock return, and $OrderImbalance_t$ is either $OIB\#_t$ or $OIB\$_t$ over the time interval t. In their original model, CRS include lagged returns as an additional independent variable in the returns predictability model. In their subsequent work, Chordia et al. (2008) refine the model and confirm that past order flows alone without the lagged returns variable is sufficient for estimating returns predictability as an inverse indicator of market efficiency. The returns predictability model in our equation (1) reflects the basic structure of the latest Chordia et al. (2008) model.

Following Chordia et al. (2008), we compute stock returns using the bid-ask midpoints quoted at the end of the intervals. For order imbalance, we compute for each interval t two measures: the number of trades $OIB\#_t$ and the dollar trades $OIB\$_t$, which we define respectively as:

$$OIB\#_t = \left\{ \left[\begin{pmatrix} Number\, of \\ buyer\, initiated \\ trades \end{pmatrix}_t - \begin{pmatrix} Number\, of \\ seller\, initiated \\ trades \end{pmatrix}_t \right] \Big/ \begin{pmatrix} Total\, number \\ of\, trades \end{pmatrix}_t \right\} \tag{2a}$$

$$OIB\$_t = \left\{ \left[\begin{pmatrix} Dollar\, traded \\ from\, buyer \\ initiated\, trades_t \end{pmatrix} - \begin{pmatrix} Dollar\, traded \\ from\, seller \\ initiated\, trades_t \end{pmatrix} \right] \Big/ \begin{pmatrix} Total\, dollar \\ traded \end{pmatrix}_t \right\} \tag{2b}$$

We classify each trade as either a buyer-initiated or seller-initiated trade using the Lee and Ready (1991) algorithm. To identify the time interval over which order imbalances are no longer significant in explaining short-horizon returns, we repeat the estimation of equation (1) using different lengths of time in the specification of interval t. We use a total of 72 k-minute intervals, starting with the minimum length one-minute interval and ending with the maximum length 120-minute interval. The increasing lengths of the intervals are set at one-minute increments for the first 60 intervals and at five-minutes increments for the remaining 12 intervals (i.e., k = 1, 2, …, 58, 59, 60, 65, 70, 75, …, 120).

The statistical significance of the estimated coefficient of the order imbalance variable is used to identify, for each stock on each trading platform, the length of the time interval over which returns predictability is no longer significant. The approach used by CRS is to start with the shortest interval, move to the next (longer) interval one at a time, and identify the interval where order imbalance first becomes insignificant. We introduce a refinement to CRS's approach. We follow CRS and identify an interval where order imbalance first becomes insignificant. However, we use this interval only as the lower bound (LB) of a possible range of time intervals. Our refined approach involves continuing to check all the remaining longer intervals and locating an upper bound (UB) for the range. An UB is the shortest interval where order imbalance is insignificant and it meets the additional condition that order imbalance remains insignificant in each and every one of the subsequent longer intervals. Effectively, our approach of identifying the LB and UB intervals ensures that order imbalance is significant in all intervals shorter than the LB and insignificant in all intervals at and longer than the UB. In some cases, the LB and the UB converge to the same interval resulting in a measure of the speed of convergence to market efficiency equal to the length of this interval. In other cases where a range exists between the LB and the UB, we use the midpoint of the range as an estimate of the speed of convergence. In cases where the UB is above the maximum length 120-minute interval, we consider the case undecided and code the speed of convergence as a missing value.

We estimate the returns prediction model in equation (1) first with $OIB\#_t$, and then with $OIB\$_t$, and obtain two sets of the speed of convergence estimates. We then average across these two sets of estimates to obtain an overall speed (*Speed*) of convergence measure for each stock on each of the two trading platforms. At this stage of our research, we examine the speed of convergence measure separately for each platform and only for these two platforms. In this study, we do not consider the effects of other platforms and possible interaction of trader behavior across the different platforms. We leave the effects of other trading platforms and the possibility of cross-platform effects for future research.

2.2 Additional variable definitions and summary statistics

To isolate the effect of ECN on the speed of convergence to market efficiency, we focus on NYSE stocks that trade simultaneously on both Arca and the traditional NYSE platforms. Consistent with prior literature, we consider several factors that have been previously documented as significant determinants of the short-horizon return predictability from past order flows (market efficiency). For our study, we include *Price* (mean daily price), *Volume* (mean daily dollar trading volume), and *Volatility* (mean daily volatility of intraday returns) as control variables specific to the NYSE and the Arca trading platforms. To control for the informational effects, we include *PIN* (probability of informed trading), *Order_Informed* (order arrival rate of informed traders) and *Order_Uninformed* (order arrival rate of uninformed traders) derived from the trading model of Easley et al. (1996). The *PIN* estimate is designed to capture the effects and interactions between informed and uninformed traders and measure the probability that any given trade is information based. We include the order arrival rates of the informed and uninformed traders to capture any incremental explanatory power these variables may have over the *PIN* variable. As firm-specific determinants, we consider the level of institutional ownership (*%INST*, defined as the level of stock holdings by institutional investors as reported in the past year up to the end of our sample period in the 13F filings) and institutional trading activity (Δ*INST*, defined as the net change of stock holdings by institutional investors over the two quarters of our sample period as reported in the 13F filings) as proxies for investor sophistication which have been shown to be positively related to informational efficiency of prices (Boehmer and Kelley, 2009; Chung and Hrazdil, 2011). We carry out our analyses using first the Δ*INST* variable and then repeat all analyses with the *%INST* variable in place of Δ*INST*. The results are very similar and overall conclusion remains the same using *%INST* as an alternate proxy for investor sophistication. Lastly, we also control for firm size (*MCAP*, defined as market capitalization of the firm) in the multivariate analysis as another firm-specific variable.

Table 1: Summary Statistics

	Mean	Median	Standard deviation	First quartile	Third quartile
Panel A: NYSE (n = 2,041)					
Speed	26.985	19.500	23.684	8.500	38.000
Price	32.873	25.746	25.029	14.834	44.398
Volatility	0.454	0.413	0.229	0.303	0.541
Volume ($mil.)	21.657	7.453	36.913	1.794	22.207
PIN	0.127	0.109	0.102	0.082	0.147
Order_Informed	566	397	525	200	792
Order_Uninformed	887	555	966	179	1,361
Panel B: ARCA (n = 2,041)					
Speed	33.312	26.250	25.910	12.000	48.500
Price	32.870	25.746	25.029	14.832	44.388
Volatility	0.454	0.409	0.233	0.304	0.538
Volume ($mil.)	9.325	2.001	22.056	0.481	7.566
PIN	0.159	0.146	0.109	0.110	0.186
Order_Informed	429	246	494	132	495
Order_Uninformed	557	200	886	71	606
Panel C: Difference between ARCA and NYSE					
Speed	6.327 ***	5.000 ***			
Price	-0.003	-0.000			
Volatility	-0.001	-0.003 ***			
Volume ($mil.)	-12.332 ***	-5.150 ***			
PIN	0.318 ***	0.032 ***			
Order_Informed	-138 ***	-97 ***			
Order_Uninformed	-334 ***	-248 ***			
Panel D: Firm specific variables					
MCAP ($mil.) (n = 2,041)	2,509.43	809.81	4,850.69	357.03	2,257.55
ΔINST (%) (n = 1,979)	20.78	17.76	17.15	8.67	28.39

Table 1 provides comparable descriptive statistics for the 2,041 stocks (for which we can estimate *Speed*) with trades executed through NYSE (Panel A) and through Arca (Panel B). All variables are winsorized at the extreme 1% level. Panel C shows the mean and median pairwise differences in the exchange-specific variables between the two trading platforms. *, **, and *** denote the two-tail significance of the corresponding test statistics of the parametric paired t-test (for the mean difference) and the nonparametric sign rank test (for the median difference) at the 10%, 5% and 1% levels respectively. The average speed of convergence to achieve market efficiency is about 27 minutes for the NYSE trades and 33 minutes for the Arca trades. Results on tests of significance reported in Panel C indicate that the speed is significantly slower for orders routed through Arca. Of the six exchange-specific variables, trading volume and the arrival rates of both the informed and the uninformed traders are significantly higher on NYSE than on Arca; and the probability of informed trading is significantly lower on NYSE than on Arca. These results are consistent with general expectation given the high trading volume on NYSE and the fact that only institutional investors can gain direct access to Arca by becoming a sponsored participant. While the arrival rates of the informed and the uninformed traders are both lower on Arca compared to the NYSE, the proportion of informed traders relative to the uninformed is higher on Arca, which explains the higher probability of informed trading as expected. Trades executed through both exchanges have comparable levels of price and volatility. Along with means and medians, the standard deviations and the inter-quartile ranges suggest that all the variables follow normal distributions.

Panel D of Table 1 displays the summary statistics of variables on firm-specific characteristics. The average NYSE firm in our sample has market capitalization of about \$2.5 billion, with on average about 21% of the shares actively being traded by the institutional investors.

3. Multivariate Results

We run the following cross-sectional multivariate regressions to determine whether the speed of convergence to market efficiency is significantly related to the type of trading platform where orders are executed, trading costs, volatility, informational effects, and other firm characteristics:

$$\begin{aligned} Speed_i = \ & \alpha + \beta_1 ECN_i + \beta_2 Volatility_i + \beta_3 Price_i + \beta_4 Volume_i \\ & + \beta_5 PIN_i + \beta_6 Order\_Informed_i + \beta_7 Order\_Uninformed_i \\ & + \beta_8 MCAP_i + \beta_9 \Delta INST_i + \varepsilon_i \end{aligned} \quad (3)$$

The dependent variable, the speed of convergence (*Speed*), is measured in the average number of minutes that it takes for past order imbalance to lose significance in the short-horizon prediction of current returns (see section 2.1. for further details). Therefore, a lower value of the dependent variable indicates a faster speed of convergence. The cross-sectional regression results are presented in Table 2. We apply the logarithmic transformation to the variables *Price*, *Volume* and *MCAP*. For presentation, we multiply the coefficients of *Order_Informed* and *Order_Uninformed* by 10^2. Numbers in parentheses beneath the coefficients are the *t*-statistics. *, **, and *** denotes the two-tail significance at the 10%, 5% and 1% levels respectively. Models 1-9 present individually the effects of trading costs, volatility, informational effects, firm size and institutional trading activity on the speed of convergence. Models 10-17 then include various control variables together in the combined models.

Table 2: Determinants of Speed of Convergence to Efficiency: Multivariate Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	26.98*** (49.11)	35.28*** (41.01)	62.56*** (41.30)	168.2*** (81.14)	20.81*** (32.78)	42.56*** (90.46)	37.90*** (50.43)	218.7*** (42.91)	37.17*** (62.28)
ECN	6.33*** (8.14)								
Volatility		-11.30*** (-6.69)							
Price			-10.12*** (-22.07)						
Volume				-9.18*** (-67.17)					
PIN					66.68*** (18.74)		26.73*** (7.91)		
Order_Informed						-1.72*** (-13.54)	-1.70*** (-13.51)		
Order_Uninformed						-0.51*** (-7.34)	-0.40*** (-5.77)		
MCAP								-9.13*** (-37.07)	
Δ*INST*									-36.15*** (-16.32)
Adjusted R^2 (%)	1.58	1.06	10.64	52.50	8.01	27.48	28.59	25.18	6.29
N	4,082	4,082	4,082	4,082	4,082	4,082	4,082	4,082	3,958

Table 2: Continued

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Intercept	166.44*** (38.62)	166.61*** (36.60)	201.17*** (38.78)	199.28*** (37.55)	175.02*** (39.99)	175.54*** (37.94)	193.03*** (35.98)	191.78*** (34.90)
ECN	-8.16*** (-13.46)	-8.22*** (-13.46)	-9.03*** (-14.84)	-9.06*** (-14.89)	-5.20*** (-8.89)	-5.24*** (-8.89)	-5.12*** (-8.71)	-5.13*** (-8.73)
Volatility	1.01 (0.76)	1.04 (0.77)	0.83 (0.63)	0.79 (0.60)	-6.80*** (-5.47)	-6.89*** (-5.47)	-7.80*** (-6.10)	-7.84*** (-6.13)
Price	6.64*** (14.32)	6.70*** (14.35)	8.58*** (17.53)	8.61*** (17.58)				
Volume	-12.45*** (-43.86)	-12.50*** (-42.50)	-14.70*** (-42.96)	-14.61*** (-42.14)	-9.92*** (-43.55)	-9.96*** (-41.35)	-10.63*** (-40.74)	-10.56*** (-39.23)
PIN		1.75 (0.55)		5.25* (1.67)		1.23 (0.38)		3.42 (1.05)
Order_Informed			0.11 (1.13)	0.10 (1.03)			-0.16 (-1.55)	-0.16 (-1.61)
Order_Uninformed			0.46*** (8.23)	0.47*** (8.37)			0.32*** (5.62)	0.33*** (5.70)
MCAP	1.70*** (5.57)	1.72*** (5.58)	1.19*** (3.88)	1.17*** (3.83)	0.61** (2.00)	0.61** (1.99)	0.20 (0.63)	0.18 (0.59)
Δ*INST*	-7.53*** (-4.50)	-7.79*** (-4.60)	-6.09*** (-3.65)	-6.15*** (-3.68)	-11.09*** (-6.53)	-11.35*** (-6.60)	-10.78*** (-6.29)	-10.82*** (-6.32)
Adjusted R^2 (%)	58.28	58.51	59.93	59.94	56.12	56.33	56.77	56.77
N	3,958	3,958	3,958	3,958	3,958	3,958	3,958	3,958

The coefficient of *ECN* in model 1 indicates that prices on Arca take about six minutes longer to adjust to the efficient level (i.e. to achieve market efficiency), consistent with the bivariate results in Table 1. Results across models 1-9 show that, among all the explanatory variables, *Volume* is most strongly associated with *Speed* (adjusted R^2 of model 4 is over 50%, compared to the considerably lower adjusted R^2 of the other models). Models 5-7 show that *PIN* remains positive and significant even after the *Order_Informed* and *Order_Uninformed* variables are added to the regression. The substantial increase in adjusted R^2, from about 8% in model 5 to over 27% in models 6 and 7, also suggests that the two order arrival rate variables are successful in capturing incremental effects that are not picked up by the probability of informed trading measure.

In models 10-17, the adjusted R^2 increase to over 50% when we consider the combined effect of all explanatory variables on the speed of convergence. The result on *ECN* in the multivariate setting is different from our previous bivariate results in Table 1. All models consistently show that, after controlling for the effects of exchange-specific and firm-specific variables, the coefficient of *ECN* is highly significant and negative. In other words, the incremental effect of *ECN* alone (i.e., over and above all the other explanatory variables) is a faster speed of convergence to market efficiency. The sharp change in the signs of variables such as *Volatility* in models 10-13 when *Price* is added to the regression suggests that the results are affected by high multicollinearity among some of the explanatory variables. In the final four models, we remove *Price* from the regression due to its multicollinearity with other variables. There are other high intercorrelations among the explanatory variables; however, they do not pose a problem about inference of the coefficients. For example, noteworthy is a high and significant correlation between *Order_Informed* and *Order_Uninformed*; there is enough variation in these variables and their error term variances are sufficiently small, which does not pose a multicollinearity problem (for further reference, see Maddala, 1992; Cohen et al., 2003). In all the models examined, the coefficient of *Volume* has a negative sign as hypothesized and it remains significant and consistently strong across all specifications. Models 14-17 show that *Volatility* and Δ*INST* have significant negative signs, both as hypothesized. With respect to the two order arrival rate variables, we find significant effect only from *Order_Uninformed* with a positive sign suggesting that the speed of convergence is significantly slower when there are more uninformed traders in the market. Our results on the significant, positive *Order_Uninformed* and the significant, negative Δ*INST* together show a consistent picture that faster speed of convergence is associated with increased participation of sophisticated, informed traders in the market. As for the remaining explanatory variables, our results provide only very weak evidence of significant effects from the probability of informed trading and firm size (*PIN* and *MCAP*) on the speed of convergence.

Overall, although our bivariate results in Table 1 show that the NYSE trades require less time to incorporate information into prices, the multivariate analysis in Table 2 demonstrates that this faster speed of convergence is driven by the higher volume of the NYSE trades. The incremental effect of the Arca ECN platform, after controlling for the trading volume and other exchange-specific and firm-specific effects, is a significantly faster speed of convergence to market efficiency (in the magnitude of around five minutes) compared to the traditional NYSE platform.

4. Summary and Conclusions

Chordia, Roll and Subrahmanyam (2005, CRS) estimate the speed of convergence to market efficiency based on short-horizon return predictability by examining 150 of the largest and actively traded NYSE companies. We extend this analysis to a much bigger sample, consisting of 2,041 NYSE firms that were traded simultaneously on the Arca and NYSE traditional trading platforms during the first six months of 2008. We are the first to examine the relation between the trading venue of electronic communication networks (ECNs) and the corresponding informational efficiency of prices in terms of the amount of time required for prices to achieve efficiency.

In a multivariate setting, we examine various proxies for trading costs, volatility, informational effects, and institutional trading activity and their impact on the speed of convergence required to achieve market efficiency. After controlling for and documenting the effects of these variables, we provide evidence that the Arca ECN platform is associated with significantly faster speed of convergence to market efficiency.

These results have important implications for investors, listed companies, regulators and stock exchanges. Our findings provide direct answers and insights for addressing issues raised in the recent Securities and Exchange Commission (2010) concept release document. We demonstrate that the speed of convergence is a feasible measure to assess how efficiently prices respond to new information. Our results also show that the ECN platform can play a significant role and contribute positively in the price discovery process by further enhancing the speed of adjustment to new information. Whether the microstructure estimates of speed to achieve market efficiency can help evaluate market efficiency of other trading platforms remains a subject for future research.

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