# THE EFFECT OF REGULATION FAIR DISCLOSURE ON MARKET INTEGRATION

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## ABSTRACT

The recent market crises have focused interest on methods to improve the functioning of financial markets. Before implementing new regulations, it is necessary to evaluate the effects of previous regulations. Regulatory changes such as Fair Disclosure have an effect on information dissemination and price discovery. This paper uses the information share of individual markets, to measure changes in the information contribution of markets before and after implementation of Regulation Fair Disclosure. Most of the existing studies focus on the price discovery process and the information contribution or share of the individual markets. This paper uses this information share as a metric to test the effect of a particular regulation. Employing cointegration analysis, this study measures the changes in the information share, impulse response functions, and tests whether Regulation Fair Disclosure has achieved its intended goal of greater informational parity and market integration. Results show that Fair Disclosure has increased the information share of satellite markets and achieved greater market integration.

JEL: G, G12, G14, G18, G19

**KEYWORDS**: Market Integration, Information Share, Regulation Fair Disclosure, Cointegration, Informational Efficiency, Market Efficiency

# **INTRODUCTION**

Financial capital must be optimally matched with investment opportunity. This would require a financial market, in which informational asymmetries do not impede the allocation process. The parties involved in the supply or consumption of financial capital, usually the latter, may be better informed and reluctant to disclose the superior information. Therefore, the participants would require a market that does not suffer from informational asymmetries and accurately discovers the prices of securities. The accuracy of price discovery reveals how efficiently information is distributed to all participants.

The production and dissemination of information and price discovery are critical to efficient capital markets. Bernier and Mouelhi (2009) in a study that covers the years 2000-7, show that despite the apparent maturity, the Canadian stock market appears to have been inefficient. Financial markets seem to suffer from persistent informational asymmetries and regulations have been imposed in an attempt to correct them. Nevertheless, the very act of imposing regulations raises several questions. Are regulations justified in a free market? Is there a significant imperfection or externality that needs resolution through regulation? How critical is regulation for the development of equitable capital markets? Do we even need regulation? If regulations are necessary, do we adopt a minimalist approach or impose regulations to pre-empt every possible crisis.

These rules influence the introduction and impounding of new information into prices as well as the dissemination of information through markets in a fundamental way. Thus, any changes to these market-governing regulations are bound to have a profound effect on the microstructure of markets and the amount of information that is available to the participants. Edwards (2012) changes in Fed policy interest rates were transmitted into domestic short-term interest rates. An examination of the effect of regulations

is particularly relevant in the modern framework where markets have fragmented into a large number of trading venues. Though investors have a greater choice, are the different markets introducing new information and thus contributing to price discovery, or just following a dominant market? Has such proliferation improved price discovery or merely fragmented it? An important, yet less explored line of inquiry is how regulations affect the interactions of various markets and how such effects are manifested in price discovery. This study attempts to at least some of these questions by studying the impact of Regulation Fair Disclosure (Reg FD) on the information share of multiple markets trading the same asset.

The Fair Disclosure regulation states that any release of information by firm must be made simultaneously to all participants. Hitherto, firms informed a preferred group of analysts and institutional investors before informing the public. These privileged groups could trade on this information before the rest of the public knew. It is almost tantamount to trading on insider information. The preferred venue of such large informed traders has usually been the NYSE or a similar large exchange. The advance information of such groups will translate into a higher information share for their preferred market. Reg FD is specifically designed to eliminate this advantage. If it has achieved its purpose, we should see a greater parity in the information contributions across markets. An analysis of the effects of such regulations would reveal whether they work and could perhaps have policy implications.

The motivation for this paper is to provide an answer to some of these questions and perhaps to address some of the gaps in existing literature pertaining to these issues. The paper is organized as follows: Section 2 briefly discusses information flow and microstructure, Section 3 examines the relevant literature and develops testable hypotheses. In Section 4, the data and methodology are explained. Section 5 discusses the results and Section 6 concludes. Some mathematical derivations are appended in an appendix at the end of the paper.

## Information and Microstructure

The random walk would be an important and economically meaningful characterization of securities prices, particularly if any random shocks are short-lived and their effect on prices is ephemeral. The practical exigencies of trading require some structure to be imposed upon the market, i.e. some rules governing the exchange process need to be instituted. Quantities and prices cannot be continuous neither can markets operate ceaselessly. Therefore, rules specifying the discreteness of quantities, minimum price changes and market operating times need to be determined. Besides this, adequate channels for the communication and dissemination of information need to be created. This would ensure that markets are informationally efficient and securities prices reflect all available information. These constitute the rules of the game or the microstructure of the market, and will in influence the path of price evolution.

An important departure of the microstructure setting from the classical setting of trade is that it is neither unconstrained nor costless. The original random walk characterization of securities prices may seem inappropriate. But prices are determined to a significant extant by the participants' conditional expectation sequences which can be characterized as some evolving process subjected to zero-mean disturbances. Therefore, the observed price may be modeled as a random walk component, to which a trade effect is added. The random walk, being a martingale, could be interpreted as the efficient price in the classical economic sense. However, the difficulty is that it is unobservable.

Central to the classical treatment of market microstructure is the concept of an asset trading in single homogenous market. The operations of the participants provide an inflow of information into the market, which is impounded into the price of the security. This process of price discovery is one of the primary purposes of a market. This framework of a single central market is no longer relevant as trading has dispersed over several venues and the theoretical central market is, in reality, fragmented. Consequently, the process of new information in-flow has several sources.

Whereas earlier, the traded price in the single central market could be considered a good proxy for the efficient price, with fragmented information flow that is no longer the case. The efficient price is no longer observable and the processes of price discovery and price formation process need to be reassessed. The contribution of each of these individual markets to the efficient price must be measured. Besides this fragmentation, the rules by which each of these markets operates has a significant impact on the price discovery process. Therefore, the regulatory environment has a significant role in the contributions of these markets. This paper deals with the generation and impounding of new information into asset prices, and the effects of trading rules and regulations on price formation, particularly in the context of fragmented markets.

## LITERATURE REVIEW

The idea that informational dynamics of stock prices are influenced by the market microstructure, such as Bid-Ask spreads, tick size, transaction costs and trading rules of different markets can be traced back to market efficiency research (Fama 1970, Grossman 1976, Grossman and Stiglitz 1976). In fragmented markets, a dominant market seemed to provide the bulk of new information while the others, i.e. satellites have a minor or no contribution (Garbade and Silber 1979). They examine the short-run behavior of the prices of same or identical assets traded on the NYSE and regional exchanges and find that the regional markets are satellites but not pure satellites (i.e. perfectly integrated markets). Empirical examination of dealer markets showed that dealers use information from other dealers besides their own estimates and that the average price does not contain all the information (Garbade, Pomerenze and Silber 1979). Information content of trade-size and direction are examined by models where the direction of trades is an autoregressive process (Glosten and Harris 1988, Madhavan, Richardson and Roomans 1997). Madhavan et al. are motivated by the idea that Buys follow Buys and Sells follow Sells, i.e. a more persistent dependency than the MA specification of structural models.

The lead-lag approach between prices in the spot market and the futures market in which models assume convergence of parameters and demonstrate that the aggregation of error processes do not converge (Stoll and Whaley 1990). The components of the Bid-Ask spread were investigated by Huang and Stoll (1996, 1997). The spread is shown to be a purely informational phenomenon (Glosten and Milgrom 1985). Copeland and Galai (1983), Easley and O'Hara (1987) examine adverse selection. This perspective has also been examined by Kyle (1985), and Admati and Plfleiderer (1988) from a theoretical perspective. Huang and Stoll (1997) provide an explicit methodology to decompose the spread as arising from order processing, adverse information and inventory holding costs. Roll (1984) and others developed statistical models that look at serial covariance. Garman (1976) adopted the time series approach to microstructure. He models the arrival time of market orders as a Poisson process. Markets deviated from the economic theory assumption of call auction markets operating at specific times. They have become continuous in the sense that they trade asynchronously during continuous time intervals instead of synchronous trading at discrete predetermined times. However, the treatment in all these papers does not use the co-integration concept explicitly. The richer covariance structures of cointegration analysis shed greater light on the dynamics of price behavior.

It is customary to assume that, no matter how efficient markets are, insiders have superior information. Evidence suggests that investors view voluntary disclosures by management as credible information. Chen, Da and Zhao (2013) show that stock returns have a significant cash flow news component whose importance increases with the investment horizon. Capital market research has established that information disclosure decisions affect almost all market transactions. Every sphere of capital market activity such as valuation of corporate assets, corporate control, proprietary and capital costs are dependent on the quantum of information available to the market participants. As such, there is a demand for information. Management, for a variety of reasons is sometimes reluctant or tardy in disclosing

private information. Such asymmetric information problems can impede the efficient allocation of capital in a capital market economy. One solution to this problem is the creation of intermediaries such as financial analysts who engage in uncovering the private information of managers. Another is to institute regulation that forces managers into fully divulging private information.

Over time, managers have developed close relationships with groups of analysts. Some favored analysts were informed before the information was made public. The unfair timing advantage that analysts seem to enjoy gave rise to a general criticism that markets were not level playing fields. Another closely related issue is the quality of the information disclosed. In an effort to neutralize the informational advantage of analysts or other favored entities, the SEC promulgated Regulation Fair Disclosure in August 2000 and it came into force on 23 October of the same year. The regulation requires all disclosures of information to be made everyone at the same time, and prohibits an earlier practice of corporations selectively informing favored analysts and professional investors. This would level the playing field and there would be greater parity in the levels of information available to investors.

Financial analysts are engaged in evaluating information collected from both public and private sources and eventually making a recommendation. The associations developed with managers and the brokerage-firm affiliations of analysts can introduce systemic biases. Since analyst compensation is related to the trading volume and investment banking fees generated for their brokerage firms, analysts are overly enthusiastic and their forecasts are dominated by "buy" recommendations (Brown et al 1985). Lin & McNichols (1998) and Dechow et al (2000) show that analysts' forecasts tend to favor firms that have a business association with the analysts' employer. The effect of voluntary disclosure regulation on analysts is not clear. There could be two opposing effects. On one hand, the additional disclosure can increase the supply of information to the analyst and improve forecast accuracy. This would result in a demand for analyst services. On the other hand, the increased availability of information may render the analyst superfluous and reduce demand for his services. Lang & Lundholm (1993) show firms that release more information have a larger analysts' following. The forecast accuracy for these firms is higher and less volatile in revisions. Eleswarapu, Thompson and Venkataraman (2002 draft) show that after Reg FD, adverse selection costs had fallen significantly thus leading to the conclusion that Reg FD mitigated information asymmetry.

Opponents of Reg FD have argued that firms will decrease the information supplied to the market causing more noise in trading or larger pricing errors. Besides this, instead of a continuous dissemination of information through analysts, firms will choose less frequent announcements; information will be lumpier causing large price swings. The net result is to increase return volatility. Though there was an increase in volatility post FD, it is not attributable to Reg FD (Heflin, Subramanyam and Zhang 2002 working paper). They find return distributions have less kurtosis post FD and lesser extreme returns. The abnormal return volatility is in fact lesser. Opponents cannot argue that bubbles and other market shocks affect estimation of return volatility. Engsted, Pedersen and Tanggaard (2012) show that return volatility estimations are accurate even in the presence of large bubbles.

In addition, the total information flow has not decreased post FD (Zitzewitz 2002 working paper). He finds that the share of new information that is private has fallen post FD. The forecast accuracy of analysts has declined, forecast dispersion has increased, and analysts that had ties with firms had superior forecast accuracy pre-FD but could not maintain this quality after FD (Mohanram and Sunder 2006). Analysts seem to be reducing their coverage of well-followed firms and focusing their efforts on firms that had not been followed closely pre-FD. Post-FD, there seems to be a trend towards idiosyncratic information discovery. Since one of the aims of Regulation FD is to reduce information asymmetry, Sidhu, Whaley et al (2007) examine the effect of Regulation-FD on adverse selection costs. They estimate the adverse selection component of the Bid-Ask spread and find that contrary to Eleswarapu, Thompson and Venkataraman (2004) that adverse selection costs have increased and conclude that Regulation-FD

has failed to achieve its goal. There is conflicting evidence and perhaps additional investigation is necessary to establish whether FD has actually increased informational parity.

Firms had been disclosing information to selected securities analysts, investment professionals and institutional investors before publicly announcing it. This results in abnormal profits to those individuals at the cost of the public. The stated purpose of Regulation FD is to eliminate this informational advantage. Informed traders would introduce new information into their preferred markets and these markets would enjoy a greater information share. However if information is released to all the participants at the same time, then we should see a decrease in the gap between information shares of leading and satellite markets. Studies have shown that adverse selection costs have fallen due to less information asymmetry and accuracy of analysts' forecasts has decreased. The preceding discussion yields to following hypotheses.

*H1: The differences in information shares of markets will decrease significantly after Reg FD H2: Impulse response durations will not be affected by Reg FD* 

# DATA AND METHODOLOGY

The general approach of this study is a cointegration analysis of stock prices. The error-correction mechanisms proposed by Engle and Granger (1987) and Johansson (1996) capture linear adjustments whereas nonlinear adjustments may exist in which case a Threshold Error Correction model as employed by Shu-Chen Chang (2010) may be more appropriate. However, the threshold model is not applicable in this case as there are no regime shifts or momentum changes. Estimation of Error Correction Models is undoubtedly prone to specification error. As Bansal, Dittmar and Kiku (2009) show, ignoring cointegration when it does exist is an even grosser misspecification. Edwards (2012) shows that a GGM regression approach yields very similar results while Guo, Wang and Yang (2013) seem to think that full sample cointegration vector estimation will greatly reduce estimation error. The advantage of the cointegration approach is that it permits a more explicit decomposition of the covariance matrix.

# Review of Cointegration

Before describing the data, a review of cointegration would perhaps bring clarity to the subsequent discussion of the methodology used in this study. If we have a time series of prices of the same asset observed in different markets. The series are non- stationary and seemingly independent. However, they are bound by arbitrage and force the markets to reach equilibrium. This equilibrium hypothesis therefore, predicates the existence of some linear combinations of the price vectors that would be stationary. This is a classic instance of cointegration. By the Granger Representation theorem any set of cointegrated I(1) variables has an Error Correction representation.

The time-series of a random variable  $\{X_t\} = [x_1 \ x_2 \ x_3 \ \dots \ x_t]'$  is considered weakly or covariance stationary if it has a constant mean, finite variance and the covariance is a function of the "distance in time" between different observations. A set of non-stationary variables is cointegrated when some linear combination(s) of them is stationary. If we have  $\{X_t\} = [x_{1t} \ x_{2t} \ x_{3t} \ x_{4t} \ \dots \ x_{kt}]'$  is a vector of k non-stationary variables each of which is integrated of order d i.e. I(d). They are cointegrated if some linear combination(s) of them is integrated of order I(d-b) where  $b \le d$ . That is if  $\beta = [\beta_1 \ \beta_2 \ \beta_3 \ \dots]'$  is some vector of constants and if  $\beta' X_t$  is integrated of order I(d-b), then  $\{X_t\}$  is cointegrated i.e. CI(d, b) If  $\{X_t\}$  is I(1) then  $\beta' X_t$  is I(0) i.e. stationary. Let

$$Y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \cdots + \beta_k x_{kt} + e_t$$
 where  $e_t$  is a stationary process (white noise) then

 $e_t = Y_t - (\beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \cdots + \beta_k x_{kt})$ . Since  $e_t$  the RHS is also stationary

Let  $\{X_t\} = [Y_t, x_{1t}, x_{2t} \dots x_{kt}]$  then  $\beta' X_t = e_t$ . Therefore,  $\beta' X_t$  is stationary and  $\beta = [\beta_1 \beta_2 \beta_3 \dots \beta_k]'$  is a cointegrating vector. Since  $\beta$  is a linear combination any scalar multiple  $\lambda\beta$  is also a cointegrating vector. Therefore, for a given cointegrated system there is no unique cointegrating vector. We usually overcome this by normalizing the cointegrating vector by one of the parameters. Therefore, we have  $\beta = \left[1, -\frac{\beta_1}{\beta_0}, -\frac{\beta_2}{\beta_0} \dots -\frac{\beta_k}{\beta_0}\right]'$  i.e. normalized by $\beta_0$ . The long run equilibrium relationship is represented by  $Y_t - (\beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \dots \beta_k x_{kt}) = 0$  and  $e_t$  is the instantaneous deviation from equilibrium or equilibrium error. In a multivariate framework, there could be several stationary combinations of the variables and therefore several linearly independent cointegrating vectors (CIs). The number of such linearly independent cointegrating vectors is the cointegrating rank of  $X_t$ , therefore the Cointegrating Rank  $\leq (k-1)$ . In the above analysis, where  $\beta$  is a vector; we are implicitly assuming a unique cointegrating vector. However, there could be several CIs and  $\beta$  is usually a  $(k \times r)$  matrix of rank r, whose columns are cointegrating vectors.

The Granger Representation theorem states that any set of cointegrated I(1) variables has an Error Correction representation. If the components of a vector of variables  $X_t$  are cointegrated, then they tend towards a long-run equilibrium or have a stationary difference i.e. a stationary linear combination. For simplicity if  $X_t$  is bivariate i.e.  $X_t = (y_t, z_t)'$  and its components are cointegrated, then as  $y_{t-1}$  and  $z_{t-1}$  deviate from the equilibrium due to shocks  $e_{yt-1}$  and  $e_{zt-1}$ , these deviations are corrected in the next period; therefore the process can be represented as

 $\begin{bmatrix} \Delta y_t = \alpha_z (y_{t-1} - \gamma z_{t-1}) + e_{yt} \\ \Delta z_t = \alpha_y (y_{t-1} - \gamma z_{t-1}) + e_{yt} \end{bmatrix}$ 

where  $\alpha_z$  and  $\alpha_y$  are the speeds of adjustment and  $(y_{t-1} - \gamma z_{t-1})$  is the error correction term. From this analysis  $X_t = (y_t, z_t)'$  in difference form can be written as

$$\Delta X_t = \alpha \beta' X_{t-1} + e_t$$
 where  $\alpha = (\alpha_v \alpha_z)$  and  $\beta = (1, -\gamma)$ 

Since the system can now be represented as a VAR, Box-Jenkins methods could be used to include lags to arrive at a properly specified form. Formally, if a set of 'k' time series variables are integrated of order 1 i.e. I(1) and they are cointegrated, the Granger Representation Theorem states that they have the following Error Correction Representation:

 $\Delta X_t = \Gamma X_{t-1} + \sum_{i=1}^p \Gamma_i \Delta X_{t-1} + e_t$  where  $\Gamma_i$  is  $(k \ge k)$  matrix with elements  $\Gamma_{jk}(i)$  and  $\Gamma = \alpha \beta'$  is a matrix with at least one element  $\neq 0$  and  $e_t$  is k-dimensional vector of disturbances. Since  $X_t$ ,  $\sum_{i=1}^p \Gamma_i \Delta X_{t-1}$  and  $e_t$  are stationary,  $\Gamma X_{t-1}$  which is the only component which has I(I) variables must also be stationary. Therefore  $\Gamma X_{t-1}$  contains the cointegrating relationships.

The VECM is a very important way of decomposing a cointegrated system of I(1) variables into a stationary and non-stationary components. This can be shown as follows:

Let  $X_t = [X_{1t} X_{2t} X_{3t} \dots X_{kt}]$  be a k-dimensional vector of I(1) variables with t = 1, 2, 3...T. If  $X_t$  is a first order Vector Auto Regressive process then  $X_t = X_{t-1} + e_t$  where  $e_t$  is white noise i.e.  $e_t = (\varepsilon_{1t} \varepsilon_{2t} \dots \varepsilon_{kt})$ , then  $\Delta X_t = e_t$ . By the Wold Decomposition Theorem  $\Delta X_t$  has an infinite Vector Moving Average representation  $\Delta X_t = C(L)e_t$  i.e.  $\Delta X_t = c_0e_t + c_1e_{t-1} + c_2e_{t-2} \dots \dots \infty = C(L)e_t$ .

Where  $C(L) = c_0 + c_1L + c_2L^2 + c_3L^3 \dots \infty$ , L is the Lag operator and  $c_j$  is a  $(k \ge k)$  matrix of coefficients. The matrix polynomial C(L) can be written as  $C(L) = C(1) + (1-L)C^*(L)$ .

This is because C (L) =C (1) +[C (L)-C (1)]. The function [C(L)-C(1)] has a solution for the associated homogeneous form [C(L)-C(1)]=0 at L=1, therefore (1-L) is a factor and [C(L)-C(1)] can be expressed as  $(1-L)C^*(L)$  where  $C^*(L)$  is another polynomial in L.

From this we have  $\Delta X_t = C(L)e_t = C(1)e_t + (1-L)C^*(L)e_t$  or  $X_t = X_{t-1} + C(1)e_t + (1-L)C^*(L)e_t$ . By applying regularity conditions  $\operatorname{toc}_j$ ,  $(1-L)C^*(L)e_t$  can be made stationary.

Now the difference equation  $X_t = X_{t-1} + C(1)e_t + (1-L)C^*(L)e_t$  can be solved by backward substitution to produce  $X_t = X_0 + C(1)\sum_{i=1}^t e_t + (1-L)C^*(L)e_t$ . The term  $C(1)\sum_{i=1}^t e_t$  will contain the non-stationary elements i.e. the stochastic trends that cause permanent effects on  $X_t$ . The transient effects are contained in  $(1-L)C^*(L)e_t$ . It is the permanent component that is decomposed to obtain information shares.

Johansson (1991) shows that in the VMA form  $X_t = X_0 + C(1) \sum_{i=1}^t e_i + (1-L)C^*(L)e_i$ 

$$C = \beta_{\perp} \left[ \alpha_{\perp} \left( I_k - \sum_{i=1}^{p-1} C_i \right) \beta_{\perp} \right]^{-1} \alpha'_{\perp}$$

Impulse Response Functions are obtained from this VMA representation. The impulse responses are generated by imparting a unit shock to the price in one market. This shock will be communicated to the other two markets and prices will keep changing until they stabilize at a new equilibrium. The time taken for this new equilibrium to be reached is observed. While the prices are in transition, an arbitrage opportunity exists in theory, since the new information is not completely internalized.

#### Sample Selection

Since the goal of this study is to estimate the effects of Regulation FD, quotes are collected before and after the implementation of Regulation FD, which was implemented on October 23, 2000. Following Hasbrouck (1995), three months of quotes for the components of the DJIA are collected from the TAO database. However, some of the stocks are not traded on the NYSE, hence the sample covers twenty five stocks. For the pre event sample period, a three-month window from October 25 to December 24 1999 was chosen. The post implementation period sample is collected from October 25 to December 24, 2000. The choice of October to December is kept constant for both samples to eliminate any seasonal effects. The data is sampled at a frequency of one second and the time series are aligned by time stamp. The procedure is to create a series of time stamps at one-second intervals from 9:30 AM to 3:45 PM. Previous literature is concerned exclusively with information shares. This study examines the changes in information share levels. The purpose is to examine whether regulations have achieved their avowed purpose. Particularly in the case of FD, the parity between the information available to the public and to select experts is analyzed. It may be argued that quote data to some extent may reflect expert opinion; therefore, trades may truly reflect the information available to actual lay traders. However, trades suffer from Bid-Ask bounce and since quotes reflect an agent's willingness to trade at the quoted price, they should contain all the information of a trade.

#### Estimation

This study follows Hasbrouck (1995) and estimates a Vector Moving Average (VMA) model. The price series used for the Information Share measure consist of Bid and Ask quotes from the NYSE, Cincinnati and Boston. The basic Error Correction equation of order k can be written as

$$\Delta p_t = \gamma (z_t - \mu_z) + A_1 \Delta p_{t-1} + A_2 \Delta p_{t-2} + A_3 \Delta p_{t-3} + \dots A_k \Delta p_{t-k} + u_t$$
(1)

where  $p_t = [p_{1t} p_{2t} p_{3t}]'$  i.e there are three time series of prices from the three exchanges.  $u_t$  is the vector of iid disturbances with covariance  $E[u_t u'_t] = \Omega$ ,  $\gamma(z_t - \mu_z)$  consists of  $\gamma$  which is the vector of the coefficients of the speed-of adjustment,  $\mu_z$  is the long-term mean value of the efficient price and  $z_t$  is the matrix of cointegrating vectors. That is

 $Z_t = \begin{bmatrix} p_{1t} - p_{2t} \\ p_{1t} - p_{3t} \end{bmatrix} = Fp_t$  where  $F = [i - I_2]$  where *i* is a vector of ones and *I* is an identity matrix. The model represented by Eq.1 is the Vector Error Correction Model (VECM). The VMA representation of the model is

 $\Delta p_t = B_0 u_t + B_1 u_{t-1} + B_2 u_{t-2} + \cdots \quad (\text{where } B_0 = I)$ (2)

If we assume  $\Delta p_t = 0$  and  $z_t = u_t$  at times t = -1, -2, -3 ... and if at time t = 0, there is unit shock to the system  $u_0 = [1 \ 0 \ 0]'$  (i.e. a unit shock to the first price series) and since  $\Delta p_t = 0$  at t = 0 we have

$$\Delta p_0 = [1 \ 0 \ 0]'$$

$$z_0 = F \Delta p_0$$

$$\Delta p_1 = A_1 \Delta p_0 + \gamma z_0$$

$$z_1 = F \Delta p_1$$

$$\Delta p_2 = A_1 \Delta p_1 + A_2 \Delta p_0 + \gamma z_1$$

In the VMA representation the first column of  $B_0$  is  $\Delta p_0$  and the first column of  $B_1$  is  $\Delta p_1$  etc. To obtain the second column of  $B_0$ ,  $B_1$  etc. the system is forecasted for shocks  $u_0 = [0 \ 1 \ 0]$ ' and  $u_0 = [0 \ 0 \ 1]$ '. The cumulative Impulse Response Functions (C<sub>k</sub>) are given by  $C_k = \sum_{i=0}^k B_i$ . When the B's are written at the lag polynomial B (L) then C is equivalent to B (1) and the rows of C are identical. The variance of the random walk component of the prices is  $\sigma_{w}^2 = c \ \Omega c'$  (3)

The Information Share of the 
$$i^{th}$$
 market  $IS_i = \frac{c_i^2 \sigma_i^2}{\sigma_w^2}$  (4)

The covariance matrix  $\Omega$  is not diagonal; hence, a Cholesky Decomposition of all orderings of the price vector must be computed to obtain the Information for each market. We have three markets; therefore, the price vector has three rows. The price from Market 1 will first be entered into the first row and the model is estimated and the Cholesky Decomposition is obtained. Next, while holding the price in the first row the rows of other two prices are interchanged. Next, the price from Market 1 is entered in the second row, the model is estimated again, and the positions of other two prices are once again interchanged. In short, we have to estimate all the permutations. The information shares so obtained are aggregated. This method produces a maximum and minimum, these are averaged once more to produce a daily information share.

The markets open and close daily and the VECM is not valid across days because of the overnight breaks in the price paths. Consequently, the information share for each market is computed for each day of the sample period (81 days) and averaged to produce the information share for each market for one security.

### The International Journal of Business and Finance Research + VOLUME 8 + NUMBER 4 + 2014

Since we have 25 securities, these are once again aggregated to produce the information share for that market for the entire sample of 25 securities over 81 trading days. Due to several aggregations, by the Central Limit Theorem, the final information share estimates are normally distributed and as such, tests such as difference in proportions etc. are valid. The impulse responses are obtained from the Vector Moving Average representation, by imparting a unit shock to each of the markets and observing the time taken for equilibrium to be reached. The impulse response functions are aggregated similarly. The difference in the time taken before and after the implementation of Reg FD is tested for significant changes.

# **EMPIRICAL RESULTS**

The analysis assumes that the quote series are non-stationary and cointegrated. The data series were tested for unit roots with the Augmented Dickey Fuller Test and with Johansson Trace and Max-Eigen Value test for number of cointegrating vectors. All the series contained a unit root and as expected, there were two cointegrating vectors. The results have been omitted due to space considerations and since they have no direct bearing on the main objective of the paper.

### Information Share Estimates

The Hasbrouck methodology for estimating relative information share of markets is essentially a method of apportioning the variance around the efficient price to each venue. Since it has been established from the cointegration tests that there are two cointegration vectors, the different rotations will yield an estimate of the upper and lower limits of the IS information share. Both Hasbrouck (1995, 2001) and Baillie et al (2002) suggest using the midpoint as a measure of the information share. The data series consists of observations over each day and the break in trading between days imposes an estimation problem. The VECM will not hold over the trading breaks, therefore, daily estimates are aggregated over the entire sample period for both the upper and lower limits. These are further aggregated to produce a single information share estimate

The estimates of the IS information share for the 1999 Bid series and the standard errors are contained in Table 1. This is the period when Reg FD was not in force. The results show the estimates of the information share for each of the twenty five stocks at Boston, Cincinnati and the NYSE. The standard errors show that the estimates are highly significant. Not surprisingly, NYSE contributes the bulk of the new information i.e. from 80 - 95% next to NYSE, Cincinnati contributes 10 - 15% and Boston about 2 - 5% It must be noted that these measures are relative and do not actually measure the exact amount of information in the market. The measure simply decomposes the variance of the efficient price and attributes a percentage of it to each market. If more markets are included then the shares will change. This study is attempting to establish changes to shares rather than absolute information shares.

The next exhibit is Table 2, which contains the information shares for the Offer series of price quotes from 1999. Once again, we see a similar distribution of information shares between the three markets. The Boston market contributes about 6% of new information; Cincinnati impounds a slightly higher amount of new information, in the region of 11% into prices. The NYSE as expected makes the major contribution of 82-95%.

Stock	Boston		Cinci	nnati	NYSE		
	IS	Stderr	IS	Stderr	IS	Stderr	
Alcoa	0.1202	0.0112***	0.1513	0.0150***	0.7651	0.0151***	
AIG	0.1190	0.0066***	0.1505	0.0082***	0.8043	0.0072***	
Am Express	0.1300	0.0076***	0.1370	0.0069***	0.8106	0.0075***	
Boeing	0.1067	0.0137***	0.1260	0.0088***	0.7806	0.0150***	
BOA	0.0590	0.0062***	0.1149	0.0085***	0.8453	0.0099***	
Citigroup	0.0760	0.0084***	0.1177	0.0101***	0.8178	0.0119***	
Caterpillar	0.0497	0.0056***	0.1103	0.0107***	0.8513	0.0115***	
Chevron	0.0942	0.0069***	0.1554	0.0108***	0.8012	0.0095***	
Du Pont	0.0750	0.0061***	0.1381	0.0071***	0.8171	0.0081***	
Disney	0.0623	0.0067***	0.0921	0.0073***	0.8461	0.0087***	
GE	0.0968	0.0064***	0.1312	0.0122***	0.8142	0.0117***	
GM	0.1114	0.0108***	0.1209	0.0082***	0.7985	0.0121***	
Home Depot	0.0413	0.0057***	0.1122	0.0097***	0.8558	0.0102***	
IBM	0.0283	0.0045***	0.0804	0.0067***	0.8959	0.0072***	
J&J	0.0636	0.0080***	0.1208	0.0082***	0.8361	0.0087***	
JP Morgan	0.1176	0.0086***	0.1694	0.0127***	0.7788	0.0153***	
Coca-Cola	0.0102	0.0019***	0.0282	0.0063***	0.6898	0.0140***	
McDonald	0.0982	0.0144***	0.1468	0.0106***	0.7668	0.0153***	
3M	0.1187	0.0072***	0.1314	0.0077***	0.8125	0.0079***	
Merck	0.0656	0.0129***	0.1075	0.0088***	0.8402	0.0144***	
Pfizer	0.0927	0.0099***	0.1201	0.0148***	0.7907	0.0151***	
P&G	0.1042	0.0074***	0.1275	0.0076***	0.8162	0.0076***	
AT&T	0.0394	0.0057***	0.0757	0.0069***	0.8861	0.0088***	
UTX	0.1032	0.0107***	0.1377	0.0133***	0.7942	0.0132***	
Wal-Mart	0.0370	0.0051***	0.0818	0.0060***	0.8850	0.0074***	

Table 1: Information Shares for 1999 Bid Series

The table shows the Information Shares of 1999 Bid Series of Price quotes for each of the stocks in the three markets being analyzed. For each market, the first column contains the information share which is the midpoint of the maximum and minimum estimates of the information share and the second column is the standard error of the estimate. \*, \*\* and \*\*\* show significance at the 10%, 5% and 1% levels respectively.

The next two tables that follow i.e. Table 3 and Table 4 contain the Information Share contributions estimated from the 2000 Bid and Offer series. These quotes are from the period after Regulation Fair Disclosure has been implemented. As expected Boston's Information share has increased significantly to about 11%. Surprisingly Cincinnati's share has fallen to 7% while the NYSE even after a reduction still maintains its leadership position at about 83%.

Stock	Boston		Cincii	nati	NYSE		
	IS	Stderr	IS	Stderr	IS	Stderr	
Alcoa	0.1137	0.0104***	0.1354	0.0132***	0.7850	0.0131***	
AIG	0.1056	0.0069***	0.1467	0.0097***	0.8142	0.0087***	
Am Express	0.1067	0.0079***	0.1408	0.0077***	0.8127	0.0077***	
Boeing	0.0798	0.0116***	0.1108	0.0095***	0.8154	0.0150***	
BOA	0.0501	0.0060***	0.1390	0.0105***	0.8267	0.0110***	
Citigroup	0.0539	0.0064***	0.1222	0.0083***	0.8365	0.0094***	
Caterpillar	0.0793	0.0095***	0.1169	0.0099***	0.8157	0.0133***	
Chevron	0.1026	0.0109***	0.1236	0.0093***	0.8214	0.0127***	
Du Pont	0.0578	0.0056***	0.1406	0.0088***	0.8255	0.0090***	
Disney	0.0605	0.0080***	0.1216	0.0091***	0.8188	0.0122***	
GE	0.0778	0.0060***	0.1153	0.0060***	0.8464	0.0065***	
GM	0.0908	0.0134***	0.1209	0.0095***	0.8103	0.0140***	
Home Depot	0.0445	0.0036***	0.1253	0.0095***	0.8419	0.0100***	
IBM	0.0343	0.0041***	0.0911	0.0060***	0.8826	0.0072***	
J&J	0.0550	0.0057***	0.1156	0.0085***	0.8464	0.0096***	
JP Morgan	0.1270	0.0074***	0.1519	0.0090***	0.7911	0.0091***	
Coca-Cola	0.0462	0.0058***	0.0773	0.0067***	0.8801	0.0083***	
McDonald	0.0970	0.0122***	0.1330	0.0103***	0.7796	0.0134***	
3M	0.1188	0.0064***	0.1281	0.0097***	0.8132	0.0093***	
Merck	0.0656	0.0074***	0.1029	0.0089***	0.8398	0.0122***	
Pfizer	0.0710	0.0076***	0.1053	0.0066***	0.8276	0.0093***	
P&G	0.1013	0.0082***	0.1349	0.0081***	0.8147	0.0087***	
AT&T	0.0164	0.0030***	0.0560	0.0049***	0.9286	0.0055***	
UTX	0.0846	0.0084***	0.1144	0.0137***	0.8293	0.0129***	
Wal-Mart	0.0544	0.0073***	0.0968	0.0073***	0.8552	0.0101***	

Table 2: Information Shares for 1999 Offer Series

The table shows the Information Shares of 1999 Offer Series of Price quotes for each of the stocks in the three markets being analyzed. For each market, the first column contains the information share which is the midpoint of the maximum and minimum estimates of the information share and the second column is the standard error of the estimate. \*, \*\* and \*\*\* show significance at the 10%, 5% and 1% levels respectively.

In the next table (Table 4), we see that Cincinnati has once again lost some of its Information Share. However, as expected Boston has increased its own information contribution to the price discovery process. Whether these changes are significant or not was tested and the results are discussed subsequently.

#### Impulse Response Estimates

The Impulse Response Functions are tabulated in Tables 5 and 6. Once again, the results for all the impulse responses have not been included due to their repetitive nature. Only a representative sample of responses to a unit impulse is shown. Panel A of Table 5 shows the impact of a unit impulse to the 1999 bid series from NYSE, responses to a unit impulse to the 2000 Offer series from Boston are shown in Panel B of Table 5.

Stock	Boston		Cincir	nnati	NYSE		
	IS	Stderr	IS	Stderr	IS	Stderr	
Alcoa	0.0955	0.0094***	0.0742	0.0070***	0.8378	0.0107***	
AIG	0.1453	0.0091***	0.0353	0.0042***	0.8317	0.0094***	
Am Express	0.1082	0.0090***	0.0538	0.0053***	0.8533	0.0093***	
Boeing	0.1558	0.0160***	0.0722	0.0103***	0.7896	0.0195***	
BOA	0.0789	0.0089***	0.0352	0.0054***	0.8900	0.0101***	
Citigroup	0.0668	0.0059***	0.0555	0.0069***	0.8870	0.0079***	
Caterpillar	0.0830	0.0074***	0.0947	0.0100***	0.8286	0.0121***	
Chevron	0.1373	0.0124***	0.0957	0.0083***	0.7895	0.0125***	
Du Pont	0.0990	0.0118***	0.0754	0.0072***	0.8372	0.0119***	
Disney	0.1042	0.0120***	0.0834	0.0081***	0.8156	0.0124***	
GE	0.0562	0.0053***	0.0498	0.0051***	0.8964	0.0078***	
GM	0.0663	0.0077***	0.0729	0.0092***	0.8661	0.0113***	
Home Depot	0.0451	0.0047***	0.0733	0.0088***	0.8842	0.0101***	
IBM	0.0422	0.0038***	0.0196	0.0021***	0.9414	0.0041***	
J&J	0.1001	0.0094***	0.0860	0.0085***	0.8345	0.0105***	
JP Morgan	0.2489	0.0099***	0.0816	0.0051***	0.7352	0.0091***	
Coca-Cola	0.0922	0.0087***	0.0641	0.0069***	0.8567	0.0095***	
McDonald	0.1077	0.0121***	0.0841	0.0093***	0.8094	0.0153***	
3M	0.2265	0.0093***	0.0418	0.0038***	0.7561	0.0097***	
Merck	0.1473	0.0097***	0.0582	0.0055***	0.8142	0.0107***	
Pfizer	0.0747	0.0098***	0.0514	0.0062***	0.8753	0.0105***	
P&G	0.1146	0.0103***	0.0573	0.0053***	0.8401	0.0105***	
AT&T	0.0727	0.0091***	0.0754	0.0048***	0.8523	0.0089***	
UTX	0.1740	0.0130***	0.0651	0.0049***	0.7893	0.0132***	
Wal-Mart	0.0809	0.0093***	0.0435	0.0047***	0.8799	0.0096***	

Table 3: Information Shares for 2000 Bid Series

The table shows the Information Shares of 2000 Bid Series of Price quotes for each of the stocks in the three markets being analyzed. For each market, the first column contains the information share which is the midpoint of the maximum and minimum estimates of the information share and the second column is the standard error of the estimate. \*, \*\* and \*\*\* show significance at the 10%, 5% and 1% levels respectively.

Similarly, Panel A of Table 6 shows the responses to a unit impulse that was imparted to the 1999 Offer Series from Cincinnati and Panel B shows the results of an impulse to the 2000 NYSE Bid Series. The first column lists the names of the stocks and the next three columns show the values where convergence took place. The last column is of critical importance since it shows the number of cycles it took for convergence to be reached. These numbers seem rather large given that markets adjust within seconds. However, it must be recalled that for the sake of estimation a high level of convergence is set. In real markets convergence occurs at the minimum tick i.e. if the tick is 10 cents, then all changes take place at steps of 10 cents.

Stock	Boston		Cincia	nnati	NYSE		
	IS	Stderr	IS	Stderr	IS	Stderr	
Alcoa	0.1097	0.0135***	0.1090	0.0154***	0.7874	0.0181***	
AIG	0.1306	0.0104***	0.0449	0.0038***	0.8384	0.0094***	
Am Express	0.1278	0.0120***	0.0631	0.0062***	0.8280	0.0118***	
Boeing	0.0872	0.0092***	0.0471	0.0058***	0.8731	0.0097***	
BOA	0.0981	0.0115***	0.0351	0.0064***	0.8706	0.0124***	
Citigroup	0.0753	0.0091***	0.0615	0.0085***	0.8716	0.0119***	
Caterpillar	0.0821	0.0124***	0.0700	0.0087***	0.8490	0.0153***	
Chevron	0.1317	0.0111***	0.0781	0.0067***	0.8108	0.0119***	
Du Pont	0.0745	0.0079***	0.0747	0.0070***	0.8582	0.0106***	
Disney	0.0920	0.0128***	0.0597	0.0052***	0.8516	0.0136***	
GE	0.0673	0.0089***	0.0462	0.0045***	0.8884	0.0097***	
GM	0.0856	0.0101***	0.0580	0.0071***	0.8621	0.0108***	
Home Depot	0.0451	0.0061***	0.0607	0.0101***	0.8958	0.0114***	
IBM	0.0527	0.0049***	0.0249	0.0033***	0.9267	0.0064***	
J&J	0.0764	0.0074***	0.0783	0.0086***	0.8605	0.0106***	
JP Morgan	0.2407	0.0089***	0.0909	0.0055***	0.7451	0.0082***	
Coca-Cola	0.0615	0.0081***	0.0448	0.0051***	0.8973	0.0092***	
McDonald	0.1158	0.0121***	0.0910	0.0127***	0.7948	0.0161***	
3M	0.1945	0.0089***	0.0390	0.0053***	0.7817	0.0086***	
Merck	0.0846	0.0092***	0.0299	0.0031***	0.8904	0.0100***	
Pfizer	0.0636	0.0062***	0.0530	0.0051***	0.8843	0.0083***	
P&G	0.1041	0.0108***	0.0355	0.0045***	0.8648	0.0101***	
AT&T	0.0424	0.0043***	0.0928	0.0070***	0.8653	0.0081***	
UTX	0.1586	0.0102***	0.0662	0.0061***	0.7987	0.0116***	
Wal-Mart	0.0630	0.0077***	0.0538	0.0063***	0.8868	0.0103***	
P&G AT&T UTX Wal-Mart	0.1041 0.0424 0.1586 0.0630	0.0108*** 0.0043*** 0.0102*** 0.0077***	0.0355 0.0928 0.0662 0.0538	0.0045*** 0.0070*** 0.0061*** 0.0063***	0.8648 0.8653 0.7987 0.8868	0.0101*** 0.0081*** 0.0116*** 0.0103***	

Table 4: Information Shares for 2000 Offer Series

The table shows the Information Shares of 2000 Offer Series of Price quotes for each of the stocks in the three markets being analyzed. For each market, the first column contains the information share which is the midpoint of the maximum and minimum estimates of the information share and the second column is the standard error of the estimate. \*, \*\* and \*\*\* show significance at the 10%, 5% and 1% levels respectively.

In this econometric analysis, we are by construction making it possible to move in very small steps. These tables report how long the innovations the efficient price persisted before the system stabilized. Note that these are innovations to that efficient price and as such have a permanent effect on the long run equilibrium price. The results show that the impulses to Boston and Cincinnati do not retain much of their impact on the efficient price i.e. the shock goes down after some time to a small fraction. However, an impulse the NYSE series retains most of its effect. This is to be expected since NYSE is the dominant market where you expect informed traders to participate. Hence, any innovations in this market have a large impact on the efficient price.

Pa	nel A: Unit Ir	npulse to 1999 N	YSE Bid Series	5	Panel B: Unit Impulse to 2000 Boston Offer Series					
Stock	Nyse	Boston	Cincinnati	Period	Stock	Boston	Cincinnati	Nyse	Period	
Alcoa	0.4888	0.4887	0.4887	1,688	Alcoa	0.034	0.033	0.033	1,852	
AIG	1.0295	1.0295	1.0295	1,003	AIG	0.002	0.002	0.002	1,305	
Am Express	1.0308	1.0308	1.0308	1,298	Am Express	0.107	0.107	0.107	1,388	
Boeing	0.7626	0.744	0.7623	2,000	Boeing	0.153	0.153	0.153	1,442	
BOA	0.724	0.7239	0.724	1,840	BOA	0.005	0.009	0.006	1,978	
Citigroup	0.8334	0.833	0.8334	1,803	Citigroup	0.114	0.114	0.114	1,531	
Caterpillar	0.789	0.7888	0.789	1,922	Caterpillar	0.015	0.012	0.012	2,000	
Chevron	1.0471	1.0471	1.0471	1,452	Chevron	0.351	0.349	0.35	1,997	
Du Pont	0.9093	0.9093	0.9093	630	Du Pont	0.021	0.021	0.021	1,749	
Disney	0.7261	0.7261	0.7261	1,872	Disney	0.01	0.01	0.01	1,995	
GE	0.8257	0.8257	0.8257	479	GE	0.062	0.062	0.062	1,976	
GM	0.8158	0.8139	0.8159	1,989	GM	0.033	0.033	0.033	1,732	
Home Depot	0.8666	0.866	0.8666	1,453	Home Depot	0.042	0.042	0.042	1,557	
IBM	1.0216	1.0216	1.0216	947	IBM	0.06	0.06	0.06	899	
J&J	0.9304	0.93	0.9304	1,562	J&J	0.048	0.048	0.048	1,597	
JP Morgan	0.8798	0.8798	0.8798	1,624	JP Morgan	0.105	0.105	0.105	844	
Coca-Cola	0.8651	0.8651	0.8651	1,627	Coca-Cola	0.309	0.309	0.309	1,924	
McDonald	0.7422	0.7414	0.7422	1,686	McDonald	0.4	0.387	0.381	1,990	
3M	1.2417	1.2417	1.2417	610	3M	0.02	0.02	0.02	1,374	
Merck	0.8168	0.8169	0.8168	1,614	Merck	0.012	0.012	0.012	1,200	
Pfizer	0.9032	0.9032	0.9032	1,141	Pfizer	0.026	0.026	0.026	1,749	
P&G	0.9601	0.9601	0.9601	642	P&G	0.06	0.059	0.06	1,577	
AT&T	1.0303	1.0302	1.0303	1,478	AT&T	0.12	0.12	0.12	1,239	
UTX	0.7878	0.7873	0.7877	1,779	UTX	0.136	0.136	0.136	1,760	
WalMart	0.8871	0.887	0.8871	1,811	Wal-Mart	0.021	0.021	0.021	1,421	

Table 5: Impulse Responses of Price Series (Bid)

The table contains the impulse responses of the 1999 Bid series in Panel A and the 2000 Offer series in Panel B. The second, third and fourth columns shows the value at which the price series converged and the last column shows the time it took for convergence in all three markets, after a unit shock is imparted to each stock in one market. Period gives the number of cycles it took for convergence to occur. E.g. in Panel A at time t=0 the price of a security in all three markets is set to zero i.e.  $p_0 = [0 \ 0 \ 0]'$ . A unit impulse is imparted to the NYSE price series (say Pfizer). The price of Pfizer in NYSE now becomes one. The prices of Pfizer in the other two markets respond by rising and the price of Pfizer in NYSE falls. They finally converge at 0.9032. It took 1141 units of system time (cycles) for convergence. This is interpreted as for a given price innovation in NYSE 90.32% of its value is impounded into the efficient price permanently. Compare this to, a unit impulse to Pfizer in Bostom (Panel B). Convergence takes place at 0.026 i.e. only 2.6% of the price innovation is impounded into the efficient price and it took 1749 units of system time. We infer that the Information contribution of Boston is very small compared to NYSE in the case of Pfizer.

Formal t-tests for changes of the mean of the information share of each venue are reported in Table 7. Panel A and B contain the results of the difference in mean information share of the Bid and Offer Series respectively. From the results, it can be seen that after Reg FD was implemented that Boston has increased its information share and the change is significant at the 5% level and as predicted NYSE has lost some of its share. This is in agreement with hypothesis H1. However, the surprising result is that Cincinnati has lost some share. It seems that both NYSE and Cincinnati have lost some of their price discovery role to Boston. Nevertheless, this must be interpreted with caution since the information share measures do not measure the absolute amount of information.

Panel A: Unit Impulse to 1999 Cincinnati Offer Series					Panel B: Unit Impulse to 2000 NYSE Bid Series				
Stock	Cincinnati	Boston	Nyse	Period	Stock	Boston	Cincinnati	Nyse	Period
Alcoa	0.0438	0.0438	0.0438	2,000	Alcoa	0.703	0.702	0.703	1,930
AIG	0.0996	0.0996	0.0996	1,216	AIG	1.012	1.012	1.012	1,435
Am Express	0.309	0.309	0.309	1,294	Am Express	1.062	1.062	1.062	1,814
Boeing	0.1336	0.1336	0.1336	1,714	Boeing	0.957	0.957	0.957	1,510
BOA	0.0281	0.0281	0.0281	1,913	BOA	1	0.989	0.997	1,995
Citigroup	0.1208	0.1289	0.123	2,000	Citigroup	1.296	1.296	1.296	1,848
Caterpillar	0.0379	0.0248	0.0276	2,000	Caterpillar	0.652	0.652	0.653	1,997
Chevron	0.1683	0.1683	0.1683	1,022	Chevron	0.644	0.646	0.646	1,991
Du Pont	0.0035	0.0035	0.0035	1,761	Du Pont	0.793	0.793	0.793	1,966
Disney	0.2976	0.2976	0.2976	1,894	Disney	0.879	0.879	0.881	1,994
GE	0.0788	0.0788	0.0788	1,285	GE	0.951	0.951	0.951	1,909
GM	0.0215	0.0214	0.0215	1,959	GM	0.884	0.872	0.884	1,813
Home Depot	0.1518	0.1527	0.1518	1,892	Home Depot	0.877	0.877	0.877	1,526
IBM	0.1001	0.1001	0.1001	1,244	IBM	1.237	1.237	1.237	881
J&J	0.0426	0.0426	0.0426	1,877	J&J	1.012	1.012	1.012	1,294
JP Morgan	0.3121	0.3121	0.3121	775	JP Morgan	0.985	0.985	0.985	625
Coca-Cola	0.0717	0.071	0.0718	1,451	Coca-Cola	0.847	0.847	0.847	1,875
McDonald	0.1245	0.1243	0.1245	1,653	McDonald	0.316	0.318	0.326	1,976
3M	0.2755	0.2755	0.2755	694	3M	0.684	0.682	0.684	1,608
Merck	0.1834	0.1834	0.1834	1,755	Merck	0.811	0.811	0.811	1,205
Pfizer	0.1823	0.1823	0.1823	1,804	Pfizer	0.903	0.902	0.903	1,625
P&G	0.2018	0.2018	0.2018	1,162	P&G	0.768	0.768	0.769	1,569
AT&T	0.1301	0.1301	0.1301	1,878	AT&T	0.968	0.968	0.968	1,233
UTX	0.2296	0.2297	0.2296	1,958	UTX	1.18	1.18	1.18	1,667
WalMart	0.2238	0.2238	0.2238	1,676	WalMart	0.91	0.91	0.91	1,604

Table 6: Impulse Responses of Price Series

The table contains the impulse responses of the 1999 Offer series in Panel A and the 2000 Bid series in Panel B. The second, third and fourth columns shows the value at which the price series converged and the last column shows the time it took for convergence in all three markets, after a unit shock is imparted to each stock in one market. Period gives the number of cycles it took for convergence to occur. E.g. in Panel A at time t=0 the price of a security in all three markets is set to zero i.e.  $p_0 = [0 \ 0 \ 0]'$ . A unit impulse is imparted to the Cincinnati price series (say P&G). The price of P&G in Cincinnati now becomes one. The prices of P&G in the other two markets respond by rising and the price of P&G in Cincinnati falls. They finally converge at 0.2018. It took 1,162 units of system time (cycles) for convergence. This is interpreted as for a given price innovation in Cincinnati 20.18% of its value is impounded into the efficient price permanently. Compare this to, a unit impulse to of P&G in NYSE (Panel B). Convergence takes place at 0.768 i.e. 76.8% of the price innovation is impounded into the efficient price and it took 1,569 units of system time. We infer that the Information contribution of Cincinnati is about a fourth as compared to NYSE in the case of P&G

The effects of exchanges offering monetary incentives for order flow may also be causing this result. The changes in the duration of the impulse response functions are reported in Panels C and D. As can be seen clearly the time taken for the system to stabilize i.e. for the changes in each venue to converge has not changed significantly after Reg FD was implemented. That Reg FD has not affected the dynamics of equilibrium. This is an expected result and is in agreement with hypothesis H2.

	Panel	A: Informa	tion Share Bi	d Series		Panel B: Information Share Offer Series					
Exchange	M	ean	Difference	P-Value	Variance	Mean		Difference	P-Value	Variance	
	Pre	Post	Post - Pre		P-Value	Pre	Post	Post - Pre		P-Value	
Boston	0.0808	0.1089	0.0281	0.0276**	0.0402**	0.0758	0.0986	0.0228	0.043**	0.0216**	
Cincinnati	0.1194	0.064	-0.0554	<.0001***	0.0379**	0.1186	0.0603	-0.0583	<.0001***	0.917	
NYSE	0.816	0.7385	-0.0775	0.001***	0.0003***	0.8512	0.8303	-0.0209	0.0594*	0.1403	
Р	anel C: Imp	oulse Respo	nse Converge	ence Bid Seri	es	Panel D: Impulse Response Convergence Offer Series					
Exchange	M	ean	Difference	P-Value	Variance	M	ean	Difference	P-Value	Variance	
	Pre	Post	Post - Pre		P-Value	Pre	Post	Post - Pre		P-Value	
Boston	1,522	1,603	81	0.4413	0.4558	1,606.70	1,612.20	5.56	0.9542	0.4115	
Cincinnati	1,540.10	1,652.60	112.5	0.3032	0.3785	1,540.10	1,557.80	17.72	0.86	0.054	
NYSE	1,438	1,635.60	197.6	0.1026	0.2289	1,552.80	1,597.40	44.56	0.6797	0.029	

#### Table 7: Information Share and Convergence Times Tests

This table shows the results of the t-tests for difference in means of the Information share and the difference in mean convergence time of the three exchanges. Panel A exhibits the results of the difference in mean Information share for the Bid Series. The 1st column contains the exchange names and applies to both panels. The 2nd and 3rd columns contain the mean pre-Reg FD (1999) and post-Reg FD (2000) Information Share. The 4th column shows the difference between both the means. The 5th column shows the p-value and level of significance of this difference and the 6th column shows the p-value of the difference in mean convergence time for the Bid and Offer series respectively before and after the implementation of Red FD are shown in Panels C and D. The 2nd and 3rd columns shows the mean convergence time of the difference in variance of the two series. Shows the mean convergence time of the difference in a pre-Reg FD. The 4th column shows the difference and the 5th shows the p-value of Reg FD. The 4th column shows the difference and the 5th shows the p-value of the difference in variance of the two series. Shows the p-value of the difference in the implementation of Red FD are shown in Panels C and D. The 2nd and 3rd columns shows the p-value of the difference in variance of the two series. As with Panel and B, the names of the exchanges are included in the 1st column of Panel C and apply to both. \*, \*\* and \*\*\* show significance at the 10%, 5% and 1% levels respectively.

## SUMMARY AND CONCLUSIONS

Markets exist for the purpose of exchange of assets. The formulation of explicit rules that govern or control this process are of crucial importance to efficiently pricing traded assets. Market crashes and similar financial crises have spurred regulatory bodies into passing a raft of regulations. However, in their haste to avert the recurrence of such events, the regulators may often promulgate flawed regulation, which far from achieving any improvement, may cause harm. If left unnoticed they may precipitate the very crises that they are intended to prevent. It is imperative that mechanisms for testing newly implemented regulations should be developed.

This study is a step in that direction. It uses a rather computationally demanding methodology to investigate the informational effects of Regulation Fair Disclosure. Hitherto, firms informed a select group of persons before informing the public. The purpose of Regulation Fair Disclosure is to bring about a degree of equality in the market. The results have shown that there is reasonable evidence to conclude that Reg. FD has not been a total failure. The information share of the dominant market, i.e., the NYSE did decrease and the share of the satellite market increased. The evidence from the offer side indicates the same conclusion though not as strongly. The information share of the Cincinnati exchange has shown a decrease instead of an increase as expected. This may be because Cincinnati may be offering better incentives to brokers for order flow. It would therefore be an opportunity for future research to explicitly model for the effects of order flow. Overall, there is enough evidence to conclude that Regulation FD has been a reasonable success, if not a resounding one.

The cointegration approach used in this study is very sensitive to misspecification. This could compromise the quality of the conclusions of the research. Aligning the quotes i.e. using the previous prevailing quote in the absence of a current quote, is not a universally accepted method, though it is endorsed by one of the foremost microstructure researchers. Only three markets have been used in this

### The International Journal of Business and Finance Research + VOLUME 8 + NUMBER 4 + 2014

analysis and perhaps more price series would not only increase the accuracy of the results, but also make the conclusions more universally applicable. In defense of this choice, it should be said that these three markets have been chosen since they operate in the same time zone. Including markets that open at different times would further exacerbate the already considerable timing issues. Another limitation is the accuracy of time stamps. They determine the quality of data, and Hasbrouck has documented evidence of some inaccuracies in data recording.

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