# THE EFFECTS OF REGULATORY CHANGES ON MARKET INTEGRATION: A COINTEGRATION ANALYSIS OF INFORMATION SHARES

By

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# CHAPTER 1

# Introduction

## 1.1 Prologue

Efficient allocation of limited resources is the crucial challenge for any economy. Financial capital must be optimally matched with investment opportunity. Doing so would require a venue where suppliers and consumers of capital can meet, in short, a financial market. However, informational asymmetries and agency issues impede the allocation process. One of 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. This places the suppliers of capital at a considerable disadvantage. To optimally match capital with investment opportunity, the participants require a market not impaired by severe informational asymmetries or agency conflicts. The efficient exchange of capital depends on vehicles or financial instruments that effect the smooth transference of capital, and a market that accurately discovers the prices of these securities. Price discovery requires firstly that information be produced and secondly that this information be efficiently distributed to all participants in a timely fashion. In essence, the efficacy of price discovery reveals how effectively new information is incorporated into prices.

An important question, then, is what affects price discovery as the fundamental function of a market? Of particular interest is how competition affects price discovery. Over time, the number of markets has increased, giving investors greater choice of trading venues. This raises the question of whether such proliferation has improved price discovery. That is, are the different markets introducing new information and thus contributing to price discovery, or are most of them, just following a dominant market. Since arbitrage keeps the prices in these markets close to each other, it is possible to examine this issue through cointegration analysis. Several researchers have examined this issue of quote or trade quality in different markets. The results have shown that most new markets do contribute information, but in general the NYSE dominates.

Of course, one possible reason for varying contributions to price discovery from different markets is the cross sectional differences in their design. In broad design, markets resemble each other. The rules and regulations governing trade, such as tick-size, are uniform across markets. For the most part, these rules, like the minimum tick-size, are arbitrary and have evolved from the exigencies of actual trade. However, markets do institute some minor changes that are unique to each market, e.g., transaction costs may differ as markets compete to attract order flow. Rules that regulate trading vary across markets, for example the current NYSE circuit-breaker rules, are the result of the market crash of 1987. Not all rules are self imposed. The bitter experience of the crash of 1927 made it necessary to impose regulations to ensure against market failure and to curb some of the more egregious excesses of the participants. New regulations had to be imposed or old ones amended to meet the requirements of a changing environment. Some of these rules could possibly impede or facilitate, in a fundamental way,the introduction and impounding of new information into prices as well as the dissemination of information through markets. Thus any changes to these market-governing regulations are bound to have a profound effect on the microstructure of markets and on the amount of information that is available to the participants. Clearly this suggests an important line of research that focuses on how regulatory changes affect the functioning of markets and whether regulations actually achieve their purpose. Information flow is also a function of the way it is processed: the communication systems and physical distances that separate markets. Therefore, technological advances will also affect the impounding and dissemination of information.

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. Here, I focus on this question by examining the impact of two major regulatory changes of recent years: Regulation Fair Disclosure and the decimalization of tick-size.

### 1.2 Motivation

From the preceding discussion it is evident that information production and dissemination are critical to efficient functioning of capital markets. Despite the apparent maturity of financial markets, there are persistent market imperfections such as information asymmetry and agency conflict. These problems reflect the enduring debate between those who endorse the view that markets are self-governing and others who insist that some form of regulatory intervention is necessary. The events of the last decade have significantly strengthened argument for substantive regulatory reform. Besides this, research has established that regulation enhances the quality and credibility of information.

Remedial actions that follow financial crises usually envisage some form of new regulation. Research has endeavored to identify the market imperfections that may justify the imposition of regulations. In the first instance, is there a significant imperfection or externality that needs resolution through regulation? How critical is regulation for the development of equitable capital markets, or do we even need regulation (as one school would argue)? If we decide that regulation is necessary, do we adopt a minimalist approach, or impose regulations to pre-empt every imaginable crisis? Indiscriminate imposition of regulations, far from achieving the desired results, could further exacerbate the crisis. The regulations themselves may introduce imperfections. Several economic and systemic factors determine whether regulation is successful in mitigating some of these imperfections. It is therefore imperative that the effect of the regulations be studied. The results may not be conclusive; however such efforts would throw some light on the issue of whether existing regulation increases efficiency and what changes need to be instituted. There is a great deal left unanswered on the effectiveness of regulation. This research uses recent regulatory changes to at least partially answer some of these questions.

Two major regulatory measures that have recently affected information acquisition and generation are Decimalization of the Tick-Size and Fair Disclosure. The effect of decimalization on the spread, and its components, liquidity, volatility, transaction costs, etc., has been well documented. However, the issue of how it affects information flow and contributions to price discovery has not been adequately investigated. Decimalization provides greater incentive for information production. Smaller tick-sizes decrease the lower bounds of the bid-ask spread. The larger the spread the higher the probability that it straddles the efficient price and the lesser the incentive for information production. Narrow spreads increase the chance of the efficient price being outside the spread and provide opportunities for profit, thus motivating information production. Therefore, there is a greater incentive to uncover information with narrower spreads. This means that not only members of the larger markets but those who operate in the satellite markets will also contribute information, thus increasing the information share of the other venues.

The Fair Disclosure regulation states that any release of information by firms must be made simultaneously to all participants. Historically, firms informed a preferred group of analysts and institutional investors before informing the general 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. Regulation FD has been specifically designed to eliminate this advantage. The SEC states that (See Appendix C):

> Where this has happened, those who were privy to the information beforehand were able to make a profit or avoid a loss at the expense of those kept in the dark.... Investors who see a security's price change dramatically and only later

> are given access to the information responsible for that move rightly question whether they are on a level playing field with market insiders.... Issuer selective disclosure bears a close resemblance in this regard to ordinary "tipping" and insider trading. In both cases, a privileged few gain an informational edge – and the ability to use that edge to profit – from their superior access to corporate insiders, rather than from their skill, acumen, or diligence.

The advance information that such groups possess will translate into a higher information share for their preferred market. If Reg FD 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.

# CHAPTER 2

## Literature Review

Before embarking on any study, it is necessary to review the existing research to obtain an overview of the prevailing ideas. This not only provides a background for this study but also places it in perspective. The review discusses the important developments that are relevant to this research and attempts to trace the evolution of the field of microstructure. Seminal articles that evaluate the role of information in microstructure, the dynamics of spread components, tick-size effects, and cointegration theory are discussed in detail.

### 2.1 Information and Microstructure

The Walrasian auction framework that is implied in most financial models does not address microstructure issues. Asset prices are assumed to reach equilibrium, but the path towards equilibrium, or the question of how disequilibrium is corrected, is not considered. Classical economic theory views the market as a trading space that is unrestricted. The trading opportunities are at once unlimited and costless. These assumptions would naturally convert prices into martingale processes. In such settings, 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. But the practical exigencies of trading require some structure, in the form of restrictions, to be imposed upon the market. Some rules or agreements governing the exchange process need to be instituted. Quantities and prices cannot be continuous; neither can markets operate continuously. Therefore, rules specifying the discreteness of quantities, minimum price changes, and market operating times need to be determined. Besides this, efficient channels for the communication and dissemination of information need to be created. These will ensure that markets are informationally efficient and securities prices at all times reflect all available information. These constitute the rules of the game or the structure of the market, and will influence the path of price evolution. The study of the exchange process is the field of market microstructure. An important departure of the microstructure view of trade from the classical setting is that trading is neither unconstrained nor costless. Under this view of discontinuous and constrained trading processes, the original random walk characterization of securities prices may seem inappropriate. But prices are determined to a significant extent by the participants' conditional expectations. These expectations change as each trade introduces new information. The set of changing expectations may be viewed as time series sequences, which can be characterized as some evolving process such as a random walk with zero-mean disturbances. Therefore, the observed price, which is a function of the participants' expectations, 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. However, this framework of a single central market is now obsolete or at best a partial description of reality. 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 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 an observable function of a single market, and the processes of price discovery and price formation 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 have a significant impact on the price discovery process. Therefore, the regulatory environment has a significant role in the contributions of these markets. The focus of this paper is to study the dynamics of 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.

The earliest literature on issues of information and prices can be traced back to the market efficiency research of Fama (**?**), Grossman (**?**), and Grossman and Stiglitz (**?**). The 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.

The issue of fragmented markets was first addressed by Garbade and Silber (**?**). They examine the short-run behavior of the prices of the same or identical assets traded on different markets, in this case, the NYSE and regional exchanges. They introduce the dominant-satellite idea where one market provides the bulk of new information while the others follow. The satellite markets either have a minor contribution or none at all. If $E_k$ is the unobservable equilibrium price at the time of the K$^{th}$ transaction price $T_k$ then $T_k = E_k + u_k$ where $u_k \sim N(0, \sigma^2)$ and $E_k$ follows a random walk, i.e., $E_k = E_{k-1} + p_k$ and $p_k \sim N(0, t_k\psi^2)$ where $t_k$is the time interval between the K$^{th}$ and (K-1)$^{th}$ transaction. Garbade *et al* designate the NYSE as the benchmark or standard (dominant) market. The price variances of sequences of prices on the NYSE, for the current period, and the variances of the *immediately preceding* period are measured. Next, the current price variances of similar price sequences on a regional market are measured. If the price variances (i.e., current) of the regional market and that of the preceding NYSE sequence are less than the variances of the standard (current NYSE variances), then the regional is a satellite of NYSE. Garbade and Silber find that the regional markets are satellites but not pure satellites (i.e., perfectly integrated markets).

Garbade and Silber (**?**) did not analyze dealer markets, which differ in operation and informational dynamics from auction markets. This was addressed by Garbade, Pomerenze and Silber (**?**), who empirically examine the information content of prices in dealer markets. They model the price revision process by a dealer as $p_0 = E + u_0$ where $E$ is the efficient price and $u_0 \sim N(0, K\sigma^2)$. $K$ is a constant that depends on the confidence the dealer places on his estimate of the efficient price ( i.e., $p_0$ is an unbiased though noisy, estimator of $E$). At this point, the dealer observes prices $p_n = (p_1, p_2, \ldots, p_n)'$ posted by his competitors where any $p_i = E + u_i$ for $i = 1, 2, \ldots, n$ and $u_i \sim N(0, F\sigma^2)$. These relations can be combined into the matrix equation $P = IE + U$ where $P = (p_0, p_1, \ldots, p_n)'$, $I$ is a $(n+1)$ identity matrix and $U \sim N(0, \sigma^2\Omega)$. The elements of $\Omega$ are $\Omega_{11} = K$, $\Omega_{ii} = F$ for $i > 1$ and $\Omega_{ij} = 0$ for $i \neq j$. They find that dealers do obtain information from the prices of other dealers, but do not discard their own estimates (namely, the contribution of $p_0$ is not insignificant). They also find that the average price does not contain all the information.

The question of whether the size of a trade and its direction affect the efficient price was examined by Glosten and Harris (**?**). They proposed a model in which the efficient price innovations arise from trade size and direction:

$$m_t = m_{t-1} + w_t \tag{2.1}$$

$$w_t = u_t + q_t(\lambda_0 + \lambda_1 V_t) \tag{2.2}$$

$$p_t = m_t + q_t(c_0 + c_1 V_t) \tag{2.3}$$

where $m_t$ is the efficient price, $w_t$ is the innovation to the efficient price, $V_t$ is the trade volume, $q_t$ (= $\pm$ 1) is the direction of trade, $\lambda$ and $c$ are the information content and cost terms. Madhavan, Richardson and Roomans (**?**) use a model where the direction of trades is an autoregressive process, i.e., $q_t = \rho q_{t-1} + \nu_t$. This is motivated by the idea that Buys follow Buys and Sells follow Sells. It models a more persistent dependency than the MA specification of structural models.

The temporal aspects of inter-market price dynamics were analyzed by Stoll and Whaley (**?**). They investigate the issue of incorporating new information into prices between the spot market and the futures market. They compare the return series of the stock index and the stock index futures. In perfect markets, both of the series must be perfectly contemporaneously correlated. However, if information arrives in one market before the other, then one may lead the other in price discovery. Their methodology consists of regressing the leads and lags of one set of returns on the other. If the coefficients of the lags of one are significant, then that market leads the other, since its lags explain some the changes in the other series.

However, the treatment in all these papers does not use the co-integration concept explicitly. Though the lead-lag treatment may be used to make broad general statements about precedence in time of one market or another, such an analysis does not allow for accurate estimation of how much new information is being contributed by each market. Cointegration analysis permits the decomposition of covariance structures of price series, which can then be used to estimate the information contributions of markets. The lead-lag methodology has come under criticism by investigators such as Hasbrouck. From an econometric perspective the models are misspecified. The models estimate the parameters of the price series (of the same asset) from different markets. The misspecification arises from the underlying assumption, that these estimates will converge to single value. But it can be demonstrated that the aggregation of error processes associated with each of these price series does not converge, therefore, the assumption that the parameter estimates will tend towards a single value is incorrect.

### 2.1.1 Spreads, Information Asymmetry and Price Formation

The other sources of information regarding prices are the bid-ask spread and the tick-size. The components of the bid-ask spread were investigated by Huang and Stoll (**?**). Among the earlier papers in this area, Demsetz (**?**), Amihud and Mendelson (**?**), and Ho and Stoll (**?**) focus on inventory holding costs of market makers, while Copeland and Galai (**?**), Glosten and Milgrom (**?**), and Easley and O'Hara (**?**) look at adverse selection. **?** and others developed statistical models that look at serial covariance. Therefore, broadly speaking, these models fall into two categories: direction of trade models (i.e., whether the trade was a buy or a sell) and covariance models. Both classes of papers decompose the spread into two components and in general do not distinguish between inventory cost and adverse selection component. Huang and Stoll (**?**) compare the execution costs between dealer and auction markets, specifically between NASDAQ and NYSE. They decompose the spread into *quoted spread*, *effective spread, and realized spread* and model transaction costs as arising from these components. **?** provide an explicit methodology to decompose the spread as arising from order processing, adverse information, and inventory holding costs.

The information asymmetry component of bid-ask spreads is addressed by Bagehot (**?**), where he shows that dealers' losses to informed traders must be compensated by profits from uninformed traders. Glosten and Milgrom (**?**) consider the spread as a purely informational phenomenon. They model a pure dealer market populated with informed and pure liquidity traders trading only in market orders. The dealer (specialist) is risk-neutral and has zero expected profits. Even under these circumstances a spread will arise since the dealer needs to ensure against losses to informed traders and induce uninformed traders to participate. The dealer posts bid-ask quotes which he will set and revise according to publicly available information. If an asset has only a high value ($V^H$) and a low value ($V^L$) with the same probability, and the proportion of informed traders is $p$, then uninformed investors will trade at an average value $\overline{V} = (V^H + V^L)/2$ then the ask price,

$A = V^H p + \overline{V(1-p)}$ and the bid price $B = V^L p + \overline{V(1-p)}$ since informed investors will only transact if they think the price is either $V^H$ or $V^L$. Thus we have a spread which arises from purely informational phenomena. The adverse selection explanations for the spread have also been investigated from a theoretical perspective by Kyle (**?**), Easley and O'Hara (**?**), and Admati and Plfleiderer (**?**).

The preceding literature had not explicitly applied time-series methodologies to microstructure analysis. Garman (**?**) was the first to adopt such an approach. He models the arrival time of market orders as a Poisson process. Markets have deviated from the assumptions of classical economic theory 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 trading synchronously at discrete predetermined times. $\{N_i(t), t \in [0, \infty]\}$ where $N_i(t), \in [1, 2, 3, \ldots]$ is a Poisson process representing the accumulation of discrete time intervals at which an order is placed, i.e., an asset is demanded by an individual *i* at time *t*. If $Y_{in}(t_{in})$ is the demand of individual $i$ in his $n-$th period, then $X_i(t) = \sum\limits_{n=1}^{N_i(t)} Y_{in}(t_{in})$ represent his total demand over $[0, \infty]$. The composite stochastic process $X_i(t)$ has mean-value function $\lambda_i(t) = E[X_i(t)]$ . If there are $M$ individuals in the market, then aggregate demand processes are $N(t) = \sum\limits_{i=1}^{M} N_i(t)$ and $X(t) = \sum\limits_{i=1}^{M} \sum\limits_{n=1}^{N_i(t)} Y_{in}(t_{in})$. **?** develop a model for the unobservable fundamental price in the absence of transaction costs as follows:

$V_t$ is the unobservable fundamental price determined at time $t$, just before the posting of the bid-ask.

$$Q_t \text{ is an indicator} = \begin{cases} +1 & : \text{ if trade is buyer initiated (i.e., above spread midpoint)} \\ -1 & : \text{ if trade is seller initiated (i.e., below midpoint)} \\ 0 & : \text{ if trade is the midpoint} \end{cases} \tag{2.4}$$

$M_t$ : is the bid - ask midpoint

$P_t$ : is the observed price of transaction

$S$ : is the constant spread

$\alpha$ : is the percentage of half - spread attributable to adverse selection

$e_t$ : is the serially uncorrelated shock due to public information

$V_t = V_{t-1} + \alpha\frac{S}{2}Q_{t-1} + e_t$, the change in the fundamental price $\Delta V_t$, is explained by the two components $\alpha\frac{S}{2}Q_{t-1}$ i.e., the private information in the last trade and the public information $e_t$. Though the fundamental price is unobservable, the midpoint $M_t$ is known. $M_t = V_t + \beta\frac{S}{2}\sum_{i=1}^{t-1} Q_i$ where $\beta$ is percentage of half-spread due to inventory costs and $\sum_{i=1}^{t-1} Q_i$ is the accumulated inventory from market start to t-1, so $Q_1$ is the opening inventory. Then, $\Delta M_t = (\alpha + \beta)\frac{S}{2}Q_{t-1} + e_t$ shows that quotes are adjusted to include the information and the inventory costs of the last trade. Finally, the observed price is given as $P_t = M_t + \frac{S}{2}Q_t + \eta_t$ where the error $\eta_t$ reflects the deviation of the observed half-spread $P_t - M_t$ from the constant half - spread $fracS2$ . The final model that is estimated is $\Delta P_t = \frac{S}{2}(Q_t - Q_{t-1}) + \lambda\frac{S}{2}Q_{t-1} + e_t$.

Others that modeled the time series behavior of prices and quotes and direction of trades are Roll (**?**), Hasbrouck (**?**), (**?**), Madhavan et al. (**?**). In general the results can be summarized as follows:

i. If transaction costs are the only cause of the spread, then prices should just tend to bounce between the bid and ask. Roll (1984) shows that this induces negative autocorrelation.

ii. If asymmetric information is the sole cause of the spread, then prices would reflect just information inflow through transactions. Price will fall when a sale occurs at the bid and will rise when a purchase occurs at the ask. Since these events can occur randomly, price and quote changes will be completely random.

iii. If inventory costs are the sole cause of the spread, then the tendency is towards inventory equilibrium. When a sale occurs, the bid-ask will fall to discourage further sale and encourage purchase and vice-versa.

### 2.1.2 Tick-Size & Decimalization Studies

The literature on tick-size effects is quite large, but only the papers that deal with the informational effects are of importance to this investigation. The arguments concerning reduction of tick-size center around two positions. One side claims that smaller tick-sizes would increase competition, cause spreads to fall and result in price improvement. The other side claims that a smaller tick would make front running easier, causing a reduction in market depth. They further claim that dealers will be unwilling to display order size and will change to a market order strategy. The overall effect is to render markets less transparent. Harris (1991) shows that liquidity providers in both exchange and dealer markets prefer a small set of discrete prices, which would obviate the need for elaborate and costly negotiation, thus reducing costs. Another behavioral aspect uncovered by him is that they prefer round fractions such as halves, quarters, etc. Often they may choose a coarser grid of prices than is required by the exchange. The net effect is that prices tend to cluster around round numbers and fractions. Harris (1994) shows that as tick-size decreases, spreads fall and volume goes up. Ahn, Cao and Choe (**?**) examine the liquidity changes around the AMEX change from 1/8 to 1/16 in 1992. They found that spreads declined but volume did not go up much. Porter and Weaver (**?**) study the effect around the TSE (Toronto Stock Exchange) changing tick-size from C$0.125 to 0.05 for stocks above $ 5.00 and from C$0.05 to 0.01 for stocks below $5. Consistent with **?**, low-price and high volume stocks were most affected. Besides this, there is some evidence that prices are less sticky with smaller tick-size.

Harris (**?**) reviews arguments for and against decimalization. One view that emerges is that tick-size effect may vary by the amount of information that an exchange releases. Bessembinder (**?**) finds that as stocks go up or down through a threshold over which the tick changes, a smaller tick-size causes moderately lower transaction costs and slightly lower volatility. Price improvements must take place at the minimum tick level rather than in response to what new information dictates.

Bacidore (**?**) explicitly addresses the informational impact of decimalization. Reduction in transaction costs with smaller tick-size has been well documented. This has been interpreted as dealers enjoying higher profits due to larger spreads imposed by bigger tick-size. Bacidore argues that this implies that all other components of the spread are unchanged. But if other components changed, then narrower spreads may be attributed to such components. Bacidore (**?**) and Bessembinder (**?**) show that a part of the fall in the spread is due to reduction in the adverse selection component. However, Bacidore shows that traders are more willing to become informed as tick-size increases. In his model, the adverse selection component is proportional to the fixed cost component of the spread, but his arguments are not counter to the idea that a smaller spread generates more research. It could also be argued that wider spreads are more likely to straddle the true price and therefore there is less incentive to obtain information.

### 2.2 Regulation Fair Disclosure (FD)[1]

No matter how efficient markets are, it is assumed that insiders have superior information. Evidence suggests that investors view voluntary disclosures by management as credible information. 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, is dependent on the quantity of information available to market participants. As such, there is a demand

[1] Documentation on Regulation FD is in Appendix A

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 intermediaries such as financial analysts who engage in uncovering the private information of managers. Another is to institute regulation that forces managers to fully divulge private information. Historically managers have developed close relationships with groups of analysts. Some of the favored analysts were informed before the information was made public. This seemingly unfair timing advantage that analysts enjoyed 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. It came into force on $23^{rd}$ October of the same year. The regulation requires that all disclosures of information be made available to everyone simultaneously, and it prohibits the earlier practice of corporations selectively informing favored analysts and professional investors. The effect of this regulation would be to level the playing field, and there would be greater parity in the levels of information available to investors.

### 2.2.1 Studies on Financial Intermediaries

Studies on the informational role of intermediaries have mostly focused on financial analysts. Financial analysts are engaged in evaluating information collected from both public and private sources in order to eventually make a recommendation. The results show that overall, analysts do add value to capital markets and play an important role in improving market efficiency. Barth and Hutton (**?**) show that the stock prices of firms with a larger analyst following incorporate new information significantly faster than the prices of less widely followed firms. It is expected that the accuracy of forecasts is predicated upon characteristics of analysts such as innate ability, experience, and familiarity with a particular sector or industry. Jacobs et al. (**?**) show that innate ability plays a significant role while Gilson et al. (**?**) find that industry specialization leads to more accurate forecasts.

As mentioned earlier, the associations developed with managers and the brokerage-firm affiliations of analysts can introduce systemic biases. **?** state that analysts are overly enthusiastic and their forecasts are dominated by “buy” recommendations. Furtheremore, since analyst compensation is related to the trading volume and investment banking fees generated by them for their brokerage firms, Lin and McNichols (**?**) and Dechow et al. (**?**) show that their 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. That is, the additional disclosure can increase the supply of information to the analysts and improve their forecast accuracy. This would result in a demand for analysts’ services. On the other hand, the increased availability of information may render the analyst superfluous and reduce demand for his services. Lang and Lundholm (**?**) show that firms that release more information have a larger analyst following. The forecast accuracy for these firms is higher with less volatility in revisions.

### 2.2.2 Regulation FD, Information Asymmetry and Volatility

Eleswarapu et al. (**?**) show that after Regulation FD the adverse selection costs had fallen significantly thus leading to the conclusion that the regulation reduced information asymmetry. Opponents of FD have argued that firms will decrease the information supplied to the market, causing more noise in trading or larger pricing errors. Opponents also argue that instead of a continuous dissemination of information through analysts, firms will choose less frequent announcements, and information flow will be lumpier, causing large price swings. The net result would be an increase in return volatility. Heflin, Subramanyam and Zhang (**?**) investigate the return volatility pre- and post-FD. Though they find an increase in volatility, it seems that it is not attributable to FD. They find return distributions have less kurtosis post-FD and lesser extreme returns. The *abnormal return* volatility is, in fact, lesser.

### 2.2.3 Information Flow and Analyst Forecast Accuracy Post-FD

Zitzewitz (**?**) finds that the total information flow has not decreased post-FD. He finds that the share of new information that is *private* has fallen subsequent to the implementation of FD. The forecast accuracy of analysts has declined and forecast dispersion has increased. Mohanram and Sunder (**?**) also find that analysts' forecast accuracy has fallen post-FD. Analysts that had ties with firms had superior forecast accuracy pre-FD but could not maintain this quality after FD. 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. After the imposition of 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 et al. (**?**) examine the effect of Regulation FD on adverse selection costs. They estimate the adverse selection component of the bid-ask spread and find contrary to Eleswarapu, Thompson and Venkataraman (**?**), 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 really increased informational parity.

## 2.3 Information Share of Markets

### 2.3.1 Measures of Information Share

The two information share measures that are used in this paper were developed by Hasbrouck (**?**) and Gonzalo and Granger (**?**). Hasbrouck (**?**) constructed a metric for measuring the information share of a market when a single asset is traded in several markets. When there are several price series of the same asset, they can be viewed as an unobservable efficient price plus innovations introduced into each venue where the asset is traded. The Hasbrouck method consists essentially of decomposing the variance and allocating portions of it to the various markets. A precursor to this idea was first introduced by Garbade and Silber (**?**) and Garbade et al. (**?**). The Gonzalo-Granger approach, instead of apportioning the variance of the innovations, decomposes the innovations themselves into permanent and stationary or transient effects, where the permanent effect is a measure of the new information incorporated into the price series. Booth et al. (**?**), Chu et al. (**?**), and Harris et al. (**?**) use this permanent-stationary decomposition.

### 2.3.2 Variance Decomposition (HASBROUCK) Measure

Hasbrouck uses the co-integration approach and decomposes the variance of the innovations to the vector of price variables. The Granger Representation Theorem can be used to represent a price vector as a finite Vector Error Correction Model (VECM). The covariance matrix of the VECM is decomposed into the permanent and transient shocks to the unobserved efficient price. If $P_t = (p_1, p_2, \dots, p_k)'$ is vector of $k$ price series, then a vector moving average (VMA) representation of this system is $\Delta P_t = \Psi(L)e_t$ where $\Psi(L)$ is a polynomial of lags. By backward substitution, we obtain $P_t = P_0 + \Psi(1)\sum_{i=1}^{t} e_i + \Psi^*(L)e_t$. $\Psi(1)$ is the matrix polynomial which contains the co-integrating relationships, and $\Psi^*(L)$ is such that $\Psi(L)e_t = \Psi(1) + (1 - L)\Psi^*(L)$. The information share of the $i^{\text{th}}$ market $= \frac{\psi_i^2 \Omega_{ii}}{\psi \Omega \psi'}$ where $\psi_i$ is the row vector of $\Psi(1)$ and $\Omega$ is the variance-covariance matrix. If the error terms are not correlated, then $\Omega$ is diagonal, but if they are correlated, then some of the off-diagonal elements will be non-zero and some restrictions need to be applied. The usual method is to use a Cholesky Decomposition where $\Omega = FF'$. Now the information share is $\frac{([\psi F])^2}{\psi \Omega \psi'}$. Hasbrouck finds that the NYSE contributes 92% of the innovations to the efficient price. Huang (2002) uses this measure to examine the quality of ECN quotes and finds that they do contribute new information to the efficient price. Chakraborthy et al. (**?**) also adopt this measure to investigate whether the derivatives market leads the spot market in new information.

### 2.3.3 Permanent-Transient (GONZALO-GRANGER) Measure

**?** use the permanent-stationary decomposition of the VECM to examine the price discovery in the German market, i.e., between the stock index, index futures, and index options. Chu et al. (**?**) use the same methodology to investigate price discovery between the S&P 500 index, the index futures, and the S&P Depository Receipts market. Harris et al. (**?**) examine the synchronous price series of IBM stock on several exchanges. All of these borrow the methodology of Gonzalo and Granger (G&G) (**?**) in the investigation of long memory processes. The G&G method partitions the cointegrated system vector into a permanent component and a transitory component. Let $X_t = (x_1, x_2, \ldots, x_n)'$ be a vector of cointegrated variables. Then it can be represented as $X_t = C_1 f_t + C_2 z_t$ where the permanent and transient components are $f_t, z_t$ respectively, and $C_1, C_2$ are loading matrices. We can show that $C_1 = \beta_\perp(\alpha'_\perp \beta_\perp)^{-1}$. Whereas the Hasbrouck measure focuses on partitioning the error variance, the G&G measure focuses on partitioning the co-integrated system. Yan and Zivot (**?**) compare both measures with simulated data and show that one is a scaled version of the other.

## 2.4 Time Series Theory

### 2.4.1 Cointegration

Analysis of cointegrated systems and the error-correction representation in particular were formally addressed by the seminal paper of Engle and Granger (**?**). But the concept of cointegration was first introduced by Granger (**?**). Mean-reverting or error-correcting behavior of variables was investigated by Phillips (**?**) and Sargan (**?**). Engle and Granger (**?**) show that if a set of integrated variables is cointegrated, meaning that it has a stationary linear combination, then the system has an error-correction representation. The VECM consists of an error-correction vector and a finite number of lagged variables. If $X_t$ is a $(N$x$1)$ vector of time series that is cointegrated, denoted by $CI(d, b)$ where $d = b = 1$, then some linear combination $\beta^{'} X_t$ is stationary. It represents the long-run equilibrium relationship, which can be expressed as $\beta^{'} X_t = 0$ where $\beta$ is the cointegrating vector. However, there could be more than one cointegrating relationship, and $\beta$ is often a matrix with the columns as cointegrating vectors. In practice, $\beta^{'} X_t$ is rarely in equilibrium, and $\beta^{'} X_t = z_t$ where $z_t$ is the stationary deviation from equilibrium or $z_t \sim iid(0, \sigma^2)$.

### 2.4.2 Common Trends and Identification Restrictions

The concept of a shared or common trend (the unobservable efficient price is the common stochastic trend) of cointegrated variables was addressed by Stock and Watson (**?**). They provide a methodology to test for the number of common trends, i.e., the order of integration. Sims (**?**) addresses questions of identification in large systems and offers methods of recovery of structural parameters that do not need "incredible identification restrictions.". Besides these there are several excellent textbook-level treatments of cointegration such as Hamilton (*Time Series Analysis*) or Enders (*Applied Econometric Time Series*). The textbooks that focus exclusively on cointegration are Lütkepohl (*New Introduction to Multiple Time Series analysis*), Johansen (*Likelihood-Based Inference in Cointegrated Vector Auto-Regressive Models*) and Anindya Banerjee et al. (*Cointegration, Error-Correction and the Econometric Analysis of Non-Stationary Data*). Lastly, *Long-Run Economic Relationships, Readings in Cointegration*, edited by Engle and Granger.

# CHAPTER 3

## Cointegration Analysis

### 3.1 Review of Cointegration

This study involves the analysis of the evolution of asset prices or price series in different markets. Each variable represents a time series of prices from a single market of the same asset observed over time. Therefore, we have a set of variables, each a time series representing various markets. The series are non-stationary and seemingly independent. But, they represent the price of the same asset; therefore, they are bound by arbitrage and cannot wander too far away from each other. If the price in any market wanders too far from the others, arbitrage operations force that price back into the neighborhood of the other prices. Thus arbitrage forces the prices to remain in dynamic 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. Consequently, a brief review of the analysis and econometrics of cointegrated variables would helpful in the subsequent model development and methodology.

#### 3.1.1 Cointegration and Error Correction

A collection of random variables composed of the values of $\{X_t\}$ is a time-series. $\{X_t\}$[1] $= (X_1, X_2, \ldots, X_t)'$ is considered weakly or covariance stationary if it has a constant

[1]denotes the whole time-series whereas $X_t$ or $x_t$ denotes the value at time $t$. Therefore $\{X_t\}$ can be considered a collection of random variables.

mean, finite variance, and the covariance is a function of the difference in time periods that separate different observations. If the mean has a trend, or the variance of the series does not converge to a finite value, then the series is non-stationary. A series can be non-stationary when it contains unit roots and is said to be integrated. The order of integration ‘d’ denotes that the series, described as $I(d)$, can be made stationary by differencing $d$ times.

A set of such non-stationary variables or time series is said to be cointegrated when some linear combination(s) of them is stationary. Assume a set of non stationary variables, each of which is $I(d)$. We have $\{X_t\} = (x_{1t}, x_{2t}, x_{3t}, \ldots, x_{kt})$ or a vector of $k$ non-stationary variables, each of which is integrated of order $d$. They are cointegrated if some linear combination(s) of them is integrated of order $I(d-b)$ where $b \leq d$. That is, if $\beta = (\beta_0, \beta_1, \ldots, \beta_k)^{'}$ 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 stationary or $I(0)$.

Let $Y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \ldots + \beta_k x_{kt} + e_t$ where $e_t$ is a stationary process.

Then $e_t = Y_t - (\beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \ldots + \beta_k x_{kt})$.

Therefore $Y_t - (\beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \ldots + \beta_k x_{kt})$ is stationary, since $e_t$ is stationary by definition.

Let $[Y_t, x_{1t}, x_{2t}, \ldots, x_{kt})]^{'} = X_t$ then $\beta^{'} X_t = e_t$.

Since $e_t$ is stationary $\beta^{'} X_t$ is also stationary and $\beta$ is a cointegrating vector (CI). Since $\beta$ is a linear combination then any scalar multiple $\lambda\, \beta$ is also a cointegrating vector for $\lambda \neq 0$. Consequently, the cointegrating vector is not unique. The cointegrating vector is usually normalized by one of the parameters, e.g., $\beta^{'} = \left(1, -\frac{\beta_1}{\beta_0}, -\frac{\beta_2}{\beta_0}, \ldots, -\frac{\beta_n}{\beta_0}\right)$ which is normalized by $\beta_0$. The long-run equilibrium relationship is represented by $Y_t - (\beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \ldots + \beta_k x_{kt}) = 0$ and $e_t$ is the 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. If a vector $X_t$ has $k$ integrated components then there will be a maximum of $(k-1)$ 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 $\beta$ was deemed to be a vector, we are implicitly assuming a unique cointegrating vector, but there could be several CIs, and $\beta$ is usually a $(k\mathrm{x}r)$ matrix of rank $r$, whose columns are cointegrating vectors.

### 3.2 Granger Representation Theorem[2]

The 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 which is 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 $y_{t-1}$ and $z_{t-1}$ could 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

$$\begin{aligned} l\Delta y_t &= \alpha_y(y_{t-1} - \gamma z_{t-1}) + e_{yt} \\ \Delta z_t &= \alpha_z(y_{t-1} - \gamma z_{t-1}) + e_{zt} \end{aligned} \tag{3.1}$$

where $\alpha_y$ and $\alpha_z$ are speed-of-adjustment coefficients, and $(y_{t-1} - \gamma z_{t-1})$ is the error correction term. Then $X_t = (y_t, z_t)'$ in difference form can be represented as $\Delta X_t = \alpha\beta' X_{t-1} + e_t$ where $\alpha = (\alpha_y, \alpha_z)'$ 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

[2] A formal proof of the Granger Representation Theorem is provided in Appendix B

1 and they are cointegrated, the Granger Representation Theorem states that they have the following error correction representation

$$\Delta X_t = \Gamma X_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta X_{t-1} + e_t \tag{3.2}$$

where $\Gamma_i = (k\text{x}k)$ coefficient matrix with elements $\Gamma_{jk}(i)$, $\Gamma = \alpha\beta' =$ matrix with at least one element $\neq 0$, $e_t = k$ -dimensional vector of disturbances.

Usually, since $rk(\alpha) = rk(\beta) =$ some$r < k, rk(\Gamma) = r$. Since $\Delta X_t$, $\sum_{i=1}^{p} \Gamma_i \Delta X_{t-1}$ and $e_t$ are all stationary, $\Gamma X_{t-1}$, which is the only expression that includes $I(1)$ variables, must also be stationary. Therefore, $\Gamma X_{t-1}$ contains the cointegration relations (Note: we can also have a vector of intercept terms, but since it is not necessary for the current analysis, it has been omitted).

### 3.2.1 Vector Error Correction Model (VECM)

The VECM is a very important way of decomposing a cointegrated system of $I(1)$ variables into stationary and non-stationary components. The model can be briefly described as follows: Let $X_t = (X_{1t}, X_{2t}, \ldots, X_{kt})'$ be a vector of $k$, $I(1)$ variables with $t = 1, 2, \ldots, T$. If $X_t$ is a first order vector autoregressive process, then $X_t = X_{t-1} + e_t$ where $e_t$ is a white-noise vector $e_t = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{kt})'$, then $\Delta X_t = e_t$ (Note: $X_t$ could have a drift term, but for the analysis it is not essential since it will be shown later that any deterministic trend can be purged). By the Wold Decomposition Theorem, $\Delta X_t$ has an infinite vector moving average (VMA) representation $X_t = C(L)e_t$ that is $\Delta X_t = c_0 e_t + c_1 e_{t-1} + c_2 e_{t-2}, \ldots, \infty = C(L)e_t$ where $C(L) = c_0 + c_1 L + c_2 L^2 + c_3 L^3, \ldots, \infty$ and $L$ is the lag operator and $c_j$ is a $(k\text{x}k)$ diagonal coefficient matrix:

$$c_0 = \begin{bmatrix} c_{10} & 0 & \dots & 0 \\ 0 & c_{20} & \dots & 0 \\ \dots & & & \\ 0 & 0 & \dots & c_{k0} \end{bmatrix} c_1 = \begin{bmatrix} c_{11} & 0 & \dots & 0 \\ 0 & c_{21} & \dots & 0 \\ \dots & & & \\ 0 & 0 & \dots & c_{k1} \end{bmatrix} c_j = \begin{bmatrix} c_{1j} & 0 & \dots & 0 \\ 0 & c_{2j} & \dots & 0 \\ \dots & & & \\ 0 & 0 & \dots & c_{kj} \end{bmatrix}$$

The matrix polynomial $C(L)$ can be written as $C(L) = C(1) + (1 - L)C^*(L)$, $C(L) = C(1) + [C(L) - C(1)]$. 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 to $c_i$, $(1 - L)C^*(L)e_t$ can be made stationary. 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 yield $X_t = X_0 + C(1) \sum_{i=1}^{t} e_i + (1 - L)C^*(L)e_t$. If $X_t$ contained a drift term, i.e., $X_t = a_0 + X_{t-1} + e_t$, then a deterministic drift term $a_0 t$ would appear in the solution: $X_t = a_0 t + X_0 + C(1) \sum_{i=1}^{t} e_i + (1 - L)C^*(L)e_t$. $X_0$ can be set to zero and the deterministic trend can be deducted out; this is the reason why the drift term was excluded earlier. The term $C(1) \sum_{i=1}^{t} e_i$ will contain the non-stationary elements that are the stochastic trends that cause permanent effects on $X_t$, and $(1 - L)C^*(L)e_t$ will contain the transient effects. It is the permanent component that is analyzed to obtain the impulse response functions (IRF) and their half-life. However, the transient term may provide insights into the dynamics of the cointegrated system even if the shocks are devoid of information. Recall that by the Granger Theorem the vector series $X_t$ has the form $\Delta X_t = \Gamma X_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta X_{t-1} + e_t$ where $\Gamma = \alpha\beta'$; therefore $\Delta X_t = \alpha\beta' X_{t-1} + \Gamma_1 \Delta X_{t-1} + \Gamma_2 \Delta X_{t-2} + \ldots + \Gamma_{p-1} \Delta X_{t-p+1} + e_t$. $C(z) = (1 - z)I_k - \alpha\beta' z - \sum_{i=1}^{p} \Gamma_i (1 - z) z^i$ is the characteristic polynomial whose roots lie on or outside the unit circle since $\Delta X_t$ is stationary. Therefore, $\det |C(z)| = 0$ for $z \geq 1$. Also, since the ranks of $\alpha$ and $\beta$ are equal, i.e., $rk(\alpha) = rk(\beta) = r < k, rk(\alpha\beta') = r$, the number of unit roots i.e., z = 1 is exactly $k - r$. The vector moving average form is

$$X_t = X_0 + \Gamma \sum_{i=1}^{t} e_i + \Gamma^*(L)e_t \tag{3.3}$$

Johansen (**?**) shows

$$\begin{aligned} \Gamma &= \beta_\perp \left[ \alpha_\perp \left( I_k - \sum_{i=1}^{p-1} \Gamma_i \right) \beta_\perp \right]^{-1} \alpha_\perp^{'} \\ \Gamma^*(L)e_t &= \sum_{j=0}^{\infty} \Gamma_j^* e_{t-j} \end{aligned} \tag{3.4}$$

### 3.2.2 Hasbrouck Measure

Let $P_t$ be a $(k\text{x}1)$ vector of log prices of one asset traded in $k$ markets. Since the prices are random walks, they contain a unit root and are $I(1)$ variables. But since we assume that they are cointegrated, some linear combination will be stationary. That is, $P_t = P_{t-1} + e_t$ and $\Delta P_t$ is stationary. $P_t = (p_1, p_2, \ldots, p_k)^{'}$ and $e_t = (e_{1t}, e_{2t}, \ldots, e_{kt})^{'}$ is a disturbance vector with $E(e_t) = 0$,

$$E(e_i, e_j^{'}) = \begin{cases} \Sigma & : \quad i = j \\ 0 & : \quad otherwise; \end{cases} \tag{3.5}$$

that is, the errors are uncorrelated. By the previous discussion of cointegrated systems, $\Delta P_t$ has an infinite VMA representation from a Wold decomposition:

$$\Delta P_t = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_n e_{t-n} + \ldots + \infty = \Theta(L)e_t \tag{3.6}$$

By the Granger Representation Theorem, this can be written as a VECM (Vector Error Correction Model) of some finite order $k-1$

$$\Delta P_t = \alpha[\beta' P_{t-1} - E(\beta' P_{t-1}] + \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-i} + e_t \tag{3.7}$$

where $\alpha$ is the vector of error correction coefficients, and $\beta$ is the cointegrating vector. The expression $[\beta' P_{t-1} - E(\beta' P_{t-1})]$ is the deviation in the previous period from the equilibrium value. Since $\Delta P_t = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_n e_{t-n} + \ldots + \infty = \Theta(L)e_t$, we can solve for $P_t$ by backward iterative substitution as shown earlier to obtain

$$P_t = P_0 + \Theta(1) \sum_{i=1}^{t} e_i + \Theta^*(L)e_t \tag{3.8}$$

From the factorization of $\Theta(L)e_t = \Theta(1) + (1-L)\Theta^*(L)$, $\Theta(1)$ will contain the cointegrating relationships, i.e., it has the $I(1)$ components. However, since $\Delta P_t$ is stationary, these integrated components must be purged. This is achieved by multiplying it with the cointegrating vector $\beta$, such that $\beta'\Theta(1) = 0$.

For simplicity, if $P_t$ is bivariate, i.e., $P_t = (p_{1t}, p_{2t})'$, then $\Delta P_t$ is their difference; consequently, we have a known cointegrating vector $\beta = (1, -1)'$, and, as Hasbrouck shows, the rows of $\Theta(1)$ would be identical. If this common row vector $\theta = (\theta_1, \theta_2)'$, then the stochastic trend is $\theta' e_t = \theta_1 e_{1t} + \theta_2 e_{2t}$. Therefore, $P_t = P_0 + \Theta(1) \sum_{i=1}^{t} e_i + \Theta^*(L)e_t$ can be written as

$$P_t = P_0 + \begin{bmatrix} 1 \\ 1 \end{bmatrix} x_t + \Theta^*(L)e_t \tag{3.9}$$

or $x_t = x_{t-1} + (\theta_1 e_{1t} + \theta_2 e_{2t})$ where $x_t$ is the unobserved efficient (full information) price and $(\theta_1 e_{1t} + \theta_2 e_{2t})$ is the information in-flow. The efficient price path is a random walk. The information share of each market is the share of the variance of $(\theta_1 e_{1t} + \theta_2 e_{2t})$. As defined earlier, $E(e_i e_j^{'}) = \Sigma = \theta \Sigma \theta^{'}$. Therefore, the information share of the $i^{\text{th}}$ market is

$$IS_i = \frac{\theta_i^1 \sigma_i^2}{\theta \Sigma \theta'} = \frac{\theta_i^1 \sigma_i^2}{\theta_1^1 \sigma_1^2 + \theta_2^1 \sigma_2^2}, \text{for } i = 1, 2 \tag{3.10}$$

We had assumed Eq. 3.5; this means that $\Sigma$ is a diagonal matrix. However, if the error terms are correlated, then we will have non-zero, off-diagonal elements, and restrictions need to be applied to recover the structural coefficients. The preferred method is a Cholesky Decomposition of the covariance matrix $\Sigma$. Let $\Sigma = UU^{'}$ where $U$ is a lower triangle matrix. Then $IS_i = \frac{([\theta^{'}U]_i)^2}{\theta\Sigma\theta'}$ where $[\theta^{'}U]_i$ is the $i^{\text{th}}$ element of $\theta^{'}U$. In general, if we have $k$ prices, then $P_t$ is $k$-variate $(P_t = p_{1t}, p_{2t}, \ldots, p_{kt})^{'}$. As stated earlier the cointegrating vectors and the Cholesky Decomposition are not unique. In particular the Cholesky Decomposition depends on the order in which the variables enter the price vector. Therefore, all possible permutations must be examined in the estimation of information shares.

### 3.2.3 Component Share

Gonzalo and Granger proposed another method of decomposing a vector of cointegrated variables into permanent and stationary components. They call it a P-T (Permanent-Transitory) decomposition. This method has been implemented by researchers such as Booth (**?**), Harris (**?**) and others, to develop an alternative measurement of a market's contribution to the efficient price. Gonzalo and Granger show that a cointegrated system can be decomposed into a permanent or integrated component P and a stationary (transient) component T, and that the permanent component is a linear combination of the variables in X$_t$.

Let $X_t = (x_{1t}, x_{2t}, \ldots, x_{kt})^{'}$ be a vector of $I(1)$ variables that are cointegrated. Then there exists a $(k\text{x}r)$ matrix $\beta$ where $r \leq k$ and $rk(\beta) = r$ such that $\beta^{'}X_t$ is $I(0)$. The error correction representation is as follows:

$$\Delta X_t = \gamma\beta' X_{t-1} + \sum_{i=1}^{\infty} \Gamma_i \Delta X_{t-i} + e_t \tag{3.11}$$

The vector $X_t$ can be decomposed into (k-r) I(1) components; and k stationary components therefore

$$X_t = A_1 f_t + \tilde{X}_t \tag{3.12}$$

where $A_1$ is defined such that $\beta^{'} A_1 = 0$, i.e., it is a null space of $\beta^{'}$. $f_t$ consists of the $I(1)$ common trends as defined in Stock and Watson (**?**) and is a linear combination of $X_t$. Let

$$f_t = B_1 X_t \tag{3.13}$$

substituting in Eq. 3.12 $\tilde{X}_t = (I - A_1 B_1) X_t = A_2 \beta^{'} X_t = A_2 z_t$ where $z_t = \beta^{'} X_t$. From Eq. 3.11, the only linear combinations of $X_t$ which are not affected by $\tilde{X}_t$ are
$f_t = \gamma_{\perp}^{'} X_t$. Therefore, $X_t = A_1 f_t + A_2 z_t$. The non-stationary part is $A_1 f_t$. Since $Z_t$ is stationary, it has no long-run effect on $A_1 f_t$, i.e., $Z_t$ does not Granger-cause $A_1 f_t$. Gonzalo and Granger define the components as follows: $\alpha$ is the vector of adjustment coefficients, $\beta$ is the cointegrating matrix $Y_t = \gamma^{'} X_t$ where $\gamma = (\alpha_{\perp}^{'} \beta_{\perp})^{-1} \alpha_{\perp}^{'}$ where $\alpha_{\perp}$ and $\beta_{\perp}$ are orthogonal complements of $\alpha$ and $\beta$. If, as in the previous case, $\beta = (1, -1)^{'}$ then, $\beta_{\perp} = (1, 1)^{'} = 1$ (note that 1 is a 2x1 vector of ones). Then $\gamma = (\alpha_{\perp}^{'} 1)^{-1} \alpha_{\perp}^{'}$ and the permanent component $= \gamma^{'} X_t = [(\alpha_{\perp}^{'} 1)^{-1} \alpha_{\perp}^{'}]^{'} X_t$, which is a weighted average of the vector $X_t$. The weights are $\gamma_i = \frac{\alpha_{\perp,i}}{\alpha_{\perp,1} + \alpha_{\perp,2}}$ for $i = 1, 2$. This is the component share. Therefore, the component share CS$_i = \frac{\alpha_{\perp i}}{\alpha_{\perp,1} + \alpha_{\perp,2}}$.

### 3.2.4 Comparison of the Information Measures

Though both measures are derived from the VECM, they differ in their definitions of innovations to the implicit stochastic trend. Both measures decompose the impact of shocks and allocate it to different markets. The Hasbrouck measure defines information contributions in terms of the contributions to the variance of the stochastic trend. That is, it decomposes the variance of the permanent component and allocates parts of this variance ($\psi\Omega\psi$ ) to each market. In contrast, the Gonzalo-Granger measure focuses exclusively on the error correction process. It measures only contributions to the permanent component and ignores the transitory effects. It decomposes the permanent component as a linear combination of the prices from each market with the weights being the shares of the respective markets. Though the approaches are different, De Jong (**?**) shows that both these measures are closely related.

$$P_t = P_0 + \Theta(1)\sum_{i=1}^{t} e_i + \Theta^*(L)e_t \tag{3.14}$$

We know that $\beta^{'}\Theta(1) = 0$ and $\Theta(1)\alpha = 0$ and $\Theta(1) = \beta_{\perp}\left[\alpha_{\perp}\left(I_k - \sum_{i=1}^{p-1}\Gamma_i\right)\beta_{\perp}\right]^{-1}\alpha_{\perp}^{'}$.

The permanent innovation is $(\theta_1 e_{1t} + \theta_2 e_{2t})$ =$\alpha^{'}e_t$. Therefore, $\alpha^{'} = \theta = (\theta_1, \theta_2)^{'}$ since a unit change in the permanent innovation has a one unit impact on the price vector, i.e., $\beta_{\perp}\left[\alpha_{\perp}\left(I_k - \sum_{i=1}^{p-1}\Gamma_i\right)\beta_{\perp}\right]^{-1} = 1$. Therefore, CS and IS are similar, up to a scalar multiplier in this case.

The Gonzalo-Granger representation, i.e., $X_t = A_1 f_t + \tilde{X}_t$ is a broader decomposition. The crucial difference between the two decompositions, is that though $f_t$ is a covariance stationary component, *it is not necessarily a random walk*. Therefore, it cannot be said to be an unbiased expectation of $X_t$ and its variance will not converge to that of $X_t$. Thus, the utility of this type of decomposition to microstructure studies is limited. Unless the underlying structural model is so defined that would justify such a generalization, a non-martingale component, though covariance stationary, is very limited in its application.

An empirical test of both measures was conducted in Hasbrouck (**?**) where the structural model is known. A comparative study was made of how well each procedure recovers the structural parameters of a known data-generating process. A two-market Roll Model was used for the study.

*Case I: The efficient price innovations are due to non-trade public information*

There are two markets $i$ = 1,2 that are structurally identical, and the efficient price evolves as $m_t = m_{t-1} + u_t$ $q_{it} = \pm 1$ with probability of 0.5. It is the bid-ask or buy-sell indicator $p_{it} = m_t + cq_{it}$ for $i = 1, 2, \ldots$ where $c$ is the half-spread $u_t$, $q_{1t}$ and $q_{2t}$ are uncorrelated.

Two price series $p_{1t}$ and $p_{2t}$ are generated with $c = 1$ and $\sigma_u = 1$. The series are cointegrated by construction, and the estimates of the two measures are given in Table 3.1.

Table 3.1: Markets with Public Information

| | Market 1 Price Discovery | Variance of Efficient Price Changes | First Order Autocorrelation of Efficient Price Changes |
|---|---|---|---|
| Structural Model | 50 | 1 | 0 |
| G&G Estimate | 50 | 2 | -0.25 |
| IS Estimate | 21-79 | 1.01 | 0 |

As the two markets are identical with neither market leading, their information contributions must be equal i.e., 50%, each. The G&G method correctly estimates the share, as 50%, while the Hasbrouck method estimates a fairly wide interval, but it contains the true value. Though the G&G measure was superior, it estimates the statistical properties of the common price, i.e., $f_1 = 0.5p_{1t}+0.5p_{2t}$, incorrectly as variance = 2 and covariance = -0.25, whereas they should be 1 and 0, respectively. The Hasbrouck measure accurately estimates both these parameters. Therefore, the G&G method will overestimate the volatility and autocorrelation.

*Case II: Markets with private information*

$m_t = m_{t-1} + \lambda q_{1t}$ $p_{it} = m_t + c_1 q_1 t$ and $p_{2t} = m_{t-1} + c_2 q_{2t}$ where $\lambda$ is the liquidity parameter. The second market lags the first by one period. The values of the two half-spreads and the liquidity parameters are set to unity for the structural model. The results are given in Table 3.2. In this case both methods are accurate in their estimate of information

Table 3.2: Markets with Private Information

| | Market 1 Price Discovery | Variance of Efficient Price Changes | First Order Autocorrelation of Efficient Price Changes |
|---|---|---|---|
| Structural Model | 100 | 1 | 0 |
| G&G Estimate | 98 | 4.79 | -0.39 |
| IS Estimate | 100 | 1.01 | 0 |

share but the G&G method is once again overestimating the statistical properties. The Hasbrouck bounds are very close (in fact they coincide,) and it correctly measures the variance and autocorrelation, the reason being that there is a single source of randomness, and therefore $m_t$ can be accurately recovered from price history. It is to be noted that though both methods give the same estimate of information contribution, the Hasbrouck measure's estimate of the moments of the random walk component are far more accurate and therefore would be better in forecasting.

*Case III: Markets with public and private information*

$m_t = m_{t-1} + \lambda q_{1t} + u_t$ $p_{it} = m_t + c_1 q_{1t}$ and $p_{2t} = m_{t-1} + c_2 q_{2t}$. Here, too, market 1 is the information source, with $c_1 = 1$, $c_2 = 0$ and $\lambda = 1$. The spread of market 1 is higher than market 2 since it is where informed trading takes place, and the costs of trading, monitoring and regulation are higher than in the satellite market. The results are given in Table 3.3. The Hasbrouck bounds are reasonably close, and its estimation of moments is also accurate. In contrast, the G&G method yields a gross underestimation of the information share of market 1, and in fact is far less than the lower bound of the Hasbrouck measure.

As can be seen from the foregoing results, both measures do not accurately recover

Table 3.3: Markets with Public and Private Information

| | Market 1 Price Discovery | Variance of Efficient Price Changes | First Order Autocorrelation of Efficient Price Changes |
|---|---|---|---|
| Structural Model | 100 | 2 | 0 |
| G&G Estimate | 60 | 1.98 | 0 |
| IS Estimate | 90-98 | 2.01 | 0 |

the structural information share, but the Hasbrouck measure does contain the structural parameter, and it accurately estimates the moments of the random walk. The G&G measure, on the other hand, can in some cases yield very inaccurate estimates and tends to overestimate volatility and autocorrelations. The G&G measure being a weighted average of the factor weights, is computationally simpler. Though De Jong had shown that both measures are proportional, we must note that the *changes in the G&G factor and Hasbrouck implied efficient price are not proportional.* The key difference is that the *G&G factor weights are applied to current prices whereas the Hasbrouck weights are applied to the price innovations.*

A further illustration of the relationship between the two measures is demonstrated by Baillie et al. (**?**). Whereas Hasbrouck estimates a VMA model, Baillie et al. (**?**) show the same results can be obtained from a VECM. As an illustration, take a bivariate VECM

$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i-1}^{k} A_j \Delta Y_{t-i} + \varepsilon_t$ where $Y_t = (y_{1t}, y_{2t})'$ with covariance matrix: $\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_2\sigma_1 & \sigma_1^2 \end{pmatrix}$. Hasbrouck converts this to a VMA as $\Delta Y_t = \Psi(L)\varepsilon_t$ and $\Psi(1) = \beta_\perp \Gamma \alpha'_\perp$ where $\Gamma = \left(\alpha'_\perp \left(I - \sum_{i=1}^{k} A_i\right) \beta_\perp\right)^{-1}$ [in most cases $\beta = (1, -1)'$].

Gonzalo and Granger decompose $Y_t$ as $Y_t = \Pi Y_t + A z_t$ and show that $\alpha_\perp = (\pi_1, \pi_2)'$. Therefore, if $\beta = (1, -1)'$ then $\Psi(1) = \begin{pmatrix} \psi \\ \psi \end{pmatrix} = \Gamma \begin{pmatrix} \pi_1 & \pi_2 \\ \pi_1 & \pi_2 \end{pmatrix}$ or $\frac{\psi_1}{\psi_2} = \frac{\pi_1}{\pi_2}$. If the errors are not correlated, then $\Omega$ is diagonal, and information share $S_i = \frac{{\psi_i}^2{\sigma_i}^2}{\psi\Omega\psi'}$ $= \frac{\pi_i^2\sigma_i^2}{\sum\limits_{i=1}^{2}\pi_i^2\sigma_i^2}$ or $\frac{\pi_i^2\sigma_i^2}{\sum\limits_{i=1}^{k}\pi_i^2\sigma_i^2}$ in a multivariate system. But if $\Omega$ is not diagonal, then a Cholesky Decomposition such that $\Omega = FF'$ is used, and $S_i = \frac{\left([\psi F]_i\right)^2}{\psi\Omega\psi'}$. $[\psi F]_i$ is the $i^{th}$ row of $\psi F$. If $F = \begin{pmatrix} f_{11} & 0 \\ f_{12} & f_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2\sqrt{(1-\rho^2)} \end{pmatrix}$ then $\frac{S_1}{S_2} = \frac{(\pi_1 f_{11}+\pi_2 f_{12})^2}{(\pi_2 f_{22})^2}$. Since we are considering a bivariate model, $S_1 + S_2 = 1$. Therefore,

$$\begin{aligned} S_1 &= \frac{(\pi_1 f_{11} + \pi_2 f_{12})^2}{(\pi_1 f_{11} + \pi_2 f_{12})^2 (\pi_2 f_{22})^2} \\ S_2 &= \frac{(\pi_2 f_{22})^2}{(\pi_1 f_{11} + \pi_2 f_{12})^2 (\pi_2 f_{22})^2} \end{aligned} \tag{3.15}$$

Generalizing to a k-variate system:

$$\begin{aligned} S_1 &= \frac{\left(\sum\limits_{i=1}^{k}\pi_i f_{i1}\right)^2}{\left(\sum\limits_{i=1}^{k}\pi_i f_{i1}\right)^2 + \left(\sum\limits_{i=1}^{k}\pi_i f_{i2}\right)^2 + \ldots + (\pi_k f_{kk})^2} \\ S_2 &= \frac{(\pi_k f_{kk})^2}{\left(\sum\limits_{i=1}^{k}\pi_i f_{i1}\right)^2 + \left(\sum\limits_{i=1}^{k}\pi_i f_{i2}\right)^2 + \ldots + (\pi_k f_{kk})^2} \end{aligned} \tag{3.16}$$

Since all the variables can be obtained from the estimation of a VECM, the method is relatively easier.

# CHAPTER 4

## Hypothesis Development

### 4.1 Price Discovery Decimalization and Spreads

There are several strands of literature on the informational effects of decimalization. One states that decimalization decreases transparency and information. Harris (?) had shown that limit orders decline as tick-size decreases, reducing liquidity. The prices tend to cluster, adversely affecting timely incorporation of new information.

Another view is that smaller tick-size makes incorporation of new information easier. The smallest price change that can occur will be at the minimum tick-size, rather than at levels commensurate with the quantity of new information. Therefore, if new information is not sufficient to cause a change equal to or greater than the minimum tick, price changes will occur only after sufficient information has accumulated. Therefore, smaller tick-size makes price discovery more efficient and prices will be less sticky.

Another argument is that the asymmetric information component of the spread changes with the tick. Bacidore (?) and Bessembinder (?) show that part of the fall in spreads is due to mitigation of adverse selection. Traders are more willing to become informed. Narrower spreads make it more likely that the efficient price is not within the spread, and consequently there is inducement to uncover more information. If decimalization has in fact improved incorporation of new information and prices are less sticky, we should see more frequent adjustments. However, since the information inflow into a market is not a function of tick-size, the overall amount flowing into the market may not change significantly. Decimalization should not have a significant impact on the information shares of different venues.

With smaller tick-sizes, a systemic effect may be observed. Small informational shocks which would not have moved prices would now cause changes. When larger tick-sizes are in effect, a price change in a venue must be incorporated by other markets in its entirety. For example, if a tick of 12.5 cents is in force and one venue increases its prices by this amount the other venues that wish to revise their prices must also change by the same amount or in multiples of this tick. There is no opportunity for them to compete by revising their prices gradually in small amounts. They are constrained by the minimum tick to make a change equal to the entire 12.5 cents or not at all. However, if a tick of 1 cent is available, then if one market changes its price by a large amount like 12.5 cents the other venues can gradually change their prices by one cent at a time instead of the full 12.5 cents as would have been necessary in the earlier case. This would mean that the prices will take a much longer time to converge or stabilize. The cointegrated system would take a much longer time to reach a new equilibrium level. This, in turn, will prolong the effect of any shock, and the system would oscillate longer before stabilizing. The changes to the efficient price would persist much longer, since the markets can now make a series of minor responses to a change at another venue. The effect of such a change in the microstructure can be measured by the duration of the impulse responses.These effects can be tested by following two hypotheses:

H1a: The impulse responses of the permanent components would take significantly longer periods to converge after decimalization.

H1b: The information share of markets will not be significantly affected by decimalization.

### 4.2 Information Share Distribution and Regulation FD

Historically firms disclosed 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 general public. Trading by such informed traders would introduce this new information first into their preferred markets. This would increase the information share of these markets. However, if information is released to all the participants at the same time, then we should see increased parity in the information share of markets. In general, informed traders tend to be institutional investors, investment professionals, and other such large investors, whereas uninformed investors, tend to be small investors. Though there is no compelling reason as to where informed investors trade, the order flow from small investors tends to be directed to regional exchanges. The regional exchanges offer incentives to brokers for directing order flow to the regionals. The small investors by virtue of being uninformed are more likely to be directed by their brokers to satellite exchanges. The stated purpose of Regulation FD is to eliminate the informational advantage accruing from selective disclosure. Since the privileged parties are large investors, the net effect should be a significant increase in the information share of satellites. Studies have shown that adverse selection costs have fallen due to less information asymmetry and the accuracy of analysts' forecasts has decreased, subsequent to the implementation of Reg. FD. The potential for change in information contributions of markets yields two hypotheses:

H2a: The differences in information shares of markets will decrease significantly after Reg. FD.

H2b: Impulse responses durations will not be affected by Reg. FD.

# CHAPTER 5

# Data and Methodology

## 5.1 Sample Selection

The principal aim of this study is to estimate the effects of decimalization and Regulation FD; therefore, quotes from periods before and after the implementation of these changes were used. Regulation FD was implemented on October 23, 2000, but the decimalization of stock prices was done in phases starting in August 2000, when the NYSE started trading seven stocks in decimals. Decimalization was extended to 57 stocks in September and by February of 2001 all the NYSE stocks made the changeover. The SEC mandated that all exchanges must complete the implementation by April 2001. The phased implementation of decimalization, causes an overlap in the sample. In order to separate the effects of FD and decimalization, a sample of stocks, when their quotes are not in decimals but are subject to Regulation FD, has been selected.

The sample selection methods vary across investigators. Hasbrouck (**?**) collected three months of observations for the thirty stocks of the DJIA. He then used a sampling interval of one second. The issue of the sampling rate is of considerable importance. Yan and Zivot (**?**) and Baillie et al. (**?**) have shown that the Hasbrouck measure is affected by the contemporaneous correlation between disturbances. Hence, a high sampling rate is required for the Hasbrouck measure. Huang (**?**), however, uses an interval of one minute over a period of one month. The Gonzalo-Granger measure, with its focus on error-correction mechanism, is not sensitive to contemporaneous correlation, and sampling frequency is not critical. Harris et al. (**?**), who employ this measure, introduce a method called REPLACE ALL. They observe the last exchange in their sample to open trading and take that trade and align it with the closest trades from the other exchanges. This would constitute one tuple of the time series. Then they wait for all the exchanges to trade. Once again, the last trade is selected and the nearest trades are aligned to it. Another method used by them is to minimize the time span between trades. However, there is some arbitrariness in the assignment of sequential order in both these methods. Though this is not critical to the Gonzalo-Granger measure, such an alignment process can introduce some artifacts into the Hasbrouck measure because of its sensitivity to contemporaneous correlation.

This paper follows the sampling method of Hasbrouck (**?**). Three months of quotes for the components of the DJIA are collected from the TAQ database. However, some of the stocks are not traded on the NYSE; hence, the sample covers twenty-five stocks. The pre-event sample period can be the same for measuring both effects. I chose a three-month window from October 25 to December 24, 1999 as the pre-event sample. The post-implementation period for FD is determined by the implementation of decimalization since the sample should be free of decimal effects. The period from October 25 to December 24, 2000 is a period when FD is in force but only a few stocks on the NYSE are decimalized. This period would also serve as the pre-decimalization sample. The post-decimalization sample is collected from May 25, 2001 to August 24, 2001. The choice of October to December is kept constant for the pre-FD and pre-decimalization periods to eliminate any seasonal effects.

Following Hasbrouck (**?**), 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 A.M. to 3:45 P.M. Next, the time stamps of data from TAQ are compared, and if there is a match, the associated quote is included. If not, the previous quote is still prevailing, and that is included as the observation. For example, if at 10:45:10

there is a quote of $35, this is included in the time series, but if there is no quote at that time, it means that the quote at 10:45:09 is still the prevailing quote since no impulse or innovation has entered the market. Therefore, the quote at 10:45:09 is also the quote at 10:45:10. It is possible that a quote may persist for a relatively longer period. The high sampling rate has the advantage of eliminating contemporaneous correlation. The sampling rate can be varied to examine the effects of correlation. Another sampling method used in this paper is to align data from different exchanges by minimizing the time difference between them. That is, data is merged on date and minimum time difference between observations from different exchanges. This will produce a sample similar to Harris et al. (**?**), but it will also distort the sequential order of observations.

The 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, I examine the parity between the information available to the general public and to privileged experts. 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 analysis of trades is beset by additional problems such as the bid-ask bounce. This is a critical drawback for a study that attempts to decompose the variance of prices.

## 5.2 Estimation

This study follows Hasbrouck (**?**) and estimates a VMA model, though Baillie et al. (**?**) show that information share estimates obtained from estimating a VECM are similar to those obtained from a VMA model, and as noted earlier, estimating a VECM is relatively easier. The reason is that the impulse response functions that are an essential part of this investigation, would in any case require a VMA representation.

The programs used for the estimations are modifications of the routines provided by

Hasbrouck and were used for his 2001 study of intraday price formation. The price series used for the Information Share measure (i.e., Hasbrouck measure) consist of bid and ask quotes from the NYSE as the leading exchange, with Cincinnati and Boston as the two regional exchanges. The basic error correction equation of order $k$ can be written as

$$\Delta p_t = \gamma(z_t - \mu_z) + A_1 \Delta p_{t-1} + A_2 \Delta p_{t-2} + A_3 \Delta p_{t-3} + \ldots + A_k \Delta p_{t-k} + u_t \tag{5.1}$$

where $p_t = [p_{1t}\, p_{2t}\, p_{3t}]'$ since there are three series, $u_t$ is the disturbance vector with covariance $E[u_t\, u_t^{'}] = \Omega$, $\gamma(z_t - \mu_z)$ consists of the error correction terms, and $\gamma$ is the vector of speeds of adjustment. The cointegrating vectors are in $z_t$. That is,

$$z_t = \begin{bmatrix} p_{1t} - p_{2t} \\ p_{1t} - p_{3t} \end{bmatrix} = F p_t \tag{5.2}$$

where $F = [i - I_2]$ and $i$ is a vector of ones. The VMA representation of the model is $\Delta p_t = B_0 u_t + B_1 u_{t-1} + B_2 u_{t-2} + \ldots + B_k u_{t-k}$ where $B_0 = I$. If we assume that $\Delta p_t = 0$ and $z_t = u_t$ at times $t = -1, -2, -3, \ldots$, and if at time $t = 0$ there is a unit shock $u_0 = [100]'$, then since $\Delta p_t = 0$ at $t = 0$, we have $\Delta p_0 = [1\,0\,0]'$ and

$$\begin{aligned} l z_0 &= \mu_z + F \Delta p_0 \\ \Delta p_1 &= A_1 \Delta p_0 + \gamma z_0 \\ z_1 &= z_0 + F \Delta p_1 \\ \Delta p_2 &= A_1 \Delta p_1 + A_2 \Delta p_0 + \gamma z_1 \end{aligned} \tag{5.3}$$

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 columns of $B_0$, $B_1$ etc., the system is forecasted for shocks $u_0 = [0\,1\,0]'$ and $u_0 = [1\,0\,0]'$. The cumulative impulse response functions are then $C_k = \sum_{i=0}^{k} B_k$. 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 ${\sigma_w}^2 = c\Omega c'$ and the information share of the $i^{\text{th}}$ market $IS_i = \frac{c_i^2 \sigma_i^2}{{\sigma_w}^2}$. If the covariance matrix $\Omega$ is not diagonal, then all the orderings of the Cholesky Decomposition must be computed. In this study we have three such orderings.

The code implementation is as follows. The matrix consisting of three columns of prices and the date and time stamps is first sorted by date and time. Next, a file containing pointers to the prices by time and date is constructed. This is necessary since the markets open and close daily, and the VECM is not valid across days because of the overnight breaks in the price paths. The estimation is done for each day and the results are aggregated for the entire sample. Once the price data is sorted and a pointer file has been created, a macro extracts the prices for a single day by means of the pointer file. This single-day data is then transposed, and the SAS procedure Proc Expand is used to transform the data to the required interval of one second. For example, if there is a quote for 10:15:35 and there is no quote for 10:15:36, then it can be assumed the quote prevailing at the previous second still holds. Therefore, the quote at 10:15:35 is inserted for 10:15:36 also. This further ensures that all the price vectors are of equal length. The VECM is then estimated for this set of prices, and the output is stored in a temporary directory. Next the vector moving average representation of the VECM is constructed, and the impulse response functions are obtained by Proc Model solve statement. The code for the random walk analysis computes the information shares. The whole process is looped over all the days in the dataset, and the results are aggregated with Proc Means.

The Gonzalo-Granger measure is estimated for two price series. This study investigates whether regulatory shocks such as FD and decimalization have any effect. Thus, it is sufficient to show that a regulation has had an effect or not; hence, a bivariate price vector is adequate. Since the G&G measure is a linear combination of the coefficients of the lagged variables, implementation differs in the sense that we are now estimating the weights or coefficients of the random walk component. It is not necessary to estimate the impulse response functions, which are essentially obtained from the covariance matrix.

# CHAPTER 6

## Empirical Results

This chapter describes the analysis of the data and discusses the results of the various tests conducted to establish or refute the hypotheses of this thesis. The tests can be broadly divided into two sections. The first consists of tests on the compliance of the data with the basic assumptions. The more critical tests to establish the hypotheses and discussion of results are in the next section. For ease of reference, the tables enumerating the less important results of the data compliance tests, are provided separately in Appendix A. The results of all of the tests are discussed in separate subsections.

### 6.1 Data Compliance Tests

#### 6.1.1 Unit Root Tests

The basic assumption in any analysis that employs a vector error correction model is that the data variables entering the vector must be integrated series. That is, the series must be non-stationary, containing one or more unit roots (Note: in a vector autoregressive (VAR) model the series must be stationary). $\{X_t\} = (X_1, X_2, X_3, \ldots, X_t)'$ where $\{X_t\}$ is a $n$x1 vector with $x_1$, $x_2$, $x_3$, etc., being variables representing $n$ time series. It is absolutely critical that these variables be integrated of the same order. The series are assumed to be random walks. In this case, the data represents bid and ask quotes from the Boston, Cincinnati and New York stock exchanges, and the assumption is that they are integrated of order one, i.e., $I(1)$.

The most popular method of testing for unit roots is the Augmented Dickey-Fuller (ADF) Test. A description of the test is provided in Appendix E. The test essentially regresses the first difference of the variable against a set of lagged variables of itself. The distribution of the test statistic was developed by Dickey and Fuller (1981). There are several software packages that conduct this test. The ADF tests in this thesis were conducted using EViews. Table A.1 outlines the results of the unit root tests on the data series for 1999 for the twenty-five stock quotes on three exchanges. The null hypothesis is that the series contains a unit root. The value of the test statistic and the critical values from the Dickey-Fuller distribution are set forth in the table. In all cases, i.e., for all the twenty-five stock quotes on each exchange, we cannot reject the hypothesis that they contain a unit root. Tables A.2 and A.3 describe the results of the ADF test for data from 2000 and 2001. The results are similar in that we cannot reject the null hypothesis of a unit root. The tests were actually conducted separately for the bid and ask series; these tables contain the consolidated results. The data complies with the basic requirement of being integrated of order one.

### 6.1.2 Granger Causality Tests

Subsequent to verifying that the data series are non-stationary, it is necessary to show that they are related. That is, if one series is subjected to a disturbance, the shock should be communicated to other series in the system. In other words, changes to one series cause changes in another series, or else we may have a set of unrelated non-stationary series. Unless there is causality between the series, we can model neither a VAR nor a VECM. This causal relationship is usually referred to as Granger causality.

In general, Granger causality establishes whether past innovations in one series affect the current value of another series. If such an effect exists then one series is said to Granger cause the other. Granger causality should not be confused with exogeneity. As mentioned, the past values of one series affect the current values of another series, whereas in determining exogeneity it is sufficient if there is no contemporaneous correlation. Granger causality is limited to linear causal effects. Any non-linear causality cannot be detected by these tests. If we have two series $\{X_t\}$ and $\{Z_t\}$, Granger causality examines whether past values of $\{X_t\}$ can help predict the current value of $\{Z_t\}$. The test usually takes the form of a series of F-tests. A regression of the differenced series $\{Z_t\}$ on its own lagged values is performed first, and then lagged values of $\{X_t\}$ are added to this equation to examine whether they add any explanatory power. If they do, then $\{X_t\}$ Granger-causes $\{Z_t\}$. Table A.4 shows the results of Granger causality tests on the data series for 1999. ”BBid” denotes the bid series from the Boston Stock exchange, ”CBid” stands for Cincinnati and ”NBid” for NYSE. ”BOfr”, ”COfr”, and ”NOfr” have similar interpretations. The null hypothesis of these tests is that the series in question does not Granger-cause the other. Tests were conducted in a pair-wise fashion for all the series. For brevity a synopsis of the results is provided in the table. The p-values show that the null hypothesis of no causality can be rejected in all the cases. Tables A.5 and A.6 shows the results for the 2000 and 2001 series respectively. As is noted the series do Granger-cause one another. This is also a required data characteristic.

### 6.1.3 Cointegration Tests

It is not sufficient to establish that the variables contain a unit root and are causally related. A more formal test than the preliminary Granger causality test is required to establish cointegration. After ascertaining that the data series are integrated by means of unit root tests , it is now essential to verify whether they do form a cointegrated system of variables, i.e., they share a common trend (Stock and Watson 1988). In order to be cointegrated, the quote series must share a common stochastic trend, which proxies for the unobserved efficient price. Tests are required not only to establish cointegration but also to estimate the number of cointegrating vectors that possibly exist. This is crucial since if more than one such cointegrating relationship exists, we would need to estimate all possible linear combinations of these vectors to arrive at an estimate of the information shares. This would require all possible rotations to be considered. In general, if there are $n$ series in the VECM, then a possible maximum of $(n-1)$ cointegrating vectors could exist.

Engle and Granger devised a method for verifying whether a set of non-stationary variables is cointegrated. However, this method suffers from a few drawbacks (discussed in Appendix E). The method used in this study was devised by Johansen. This methodology consists of a pair of tests called the Trace and Maximum Eigen Value Tests (a description of the tests is included in Appendix E). It is a multi-stage testing procedure, where the system of quote series is first tested under a null hypothesis of "at most one cointegrating vector". If this can be rejected, we proceed to testing under a null of "at most two cointegrating vectors" and so on. If for example, we reject the presence of "at most $n$ cointegrating vectors," but we cannot reject the null of "at most $(n+1)$ cointegrating vectors" then we may conclude that $n+1$ cointegrating vectors, exist. Table A.7 displays the results for the quote series for 1999, and the cointegrated system consists of the quote sequences from the Boston stock exchange, the Cincinnati stock exchange and the NYSE. Both Trace and Maximum Eigen Value tests show that we can reject that at most one cointegrating vector exists but we cannot reject that at most two such vectors exist. We can conclude that there are two cointegrating relationships. This is in accord with the theoretical estimate that an *n-variable* system will have at most $(n-1)$ cointegrating relationships. But more importantly, it is necessary to know that there is no unique relationship, as it is now necessary to consider the different rotations of the cointegrating vector. Tables A.8 and A.9 show the results of the tests for the quote series from 2000 and 2001. These results also lead us to the conclusion that at most two cointegrating vectors exist. This now concludes the section on tests of data compliance.

### 6.2 Information Share and Impulse Response Estimates

This and subsequent sections constitute the essence of this investigation. Two measures of information share of markets, the Hasbrouck or IS measure and the Gonzalo-Granger or G&G/PT measure, have been used in this study. The information shares estimations employ different methodologies, as their definition of information differs. However, there are some similarities, and this has been discussed earlier. The estimates of information shares by both these measures and the impulse response durations are set out and discussed in this section.

#### 6.2.1 Hasbrouck (IS) Measure of Information Share

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. From the earlier $P_t = P_0 + \Theta(1) \sum_{i=1}^{t} e_i + \Theta^*(L)e_t$ discussion on cointegration, a vector autoregressive process has an equivalent infinite vector moving average (VMA) representation. The Hasbrouck method exploits this property to initial VECM, i.e., as an equivalent VMA i.e., $P_t = P_0 + \Theta(1) \sum_{i=1}^{t} e_i + \Theta^*(L)e_t$ and the stochastic trend is $\theta' e_t = \theta_1 e_{1t} + \theta_2 e_{2t}$. The information share then can be computed as

$$\mathbf{IS_i} = \frac{\theta_i^2 \sigma_i^2}{\theta \Sigma \theta'} = \frac{\theta_i^2 \sigma_i^2}{\theta_1^2 \sigma_1^2 + \theta_2^2 \sigma_2^2} \tag{6.1}$$

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 (**??**) and Baillie et al. (**?**) 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.

The estimates of the maximum and the minimum IS information share for the 1999 bid series and the standard errors are contained in Table 7.1. This is the period when neither Reg. FD nor decimalization was implemented. The results show the estimates of the information share for each of the twenty-five stocks at the Boston stock exchange, the Cincinnati stock exchange, 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%. The next highest is Cincinnati, which contributes 10-15%, and finally Boston with 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 measures changes to the contributions of each market, rather than absolute information shares. Table 7.2 contains the information shares for the offer series from 1999. Once again, we see a similar distribution of information shares among the three markets. Tables 7.3 and 7.4 contain the estimates for the bid and ask series from 2000, which covers the period when only Reg.FD was in force. Tables 7.5 and 7.6 show the estimates from 2001, when decimalization has been fully implemented. The midpoints of these estimates will be used in tests for changes.

### 6.2.2 Gonzalo-Granger (G&G/PT) Measure of Information Share

The theoretical underpinnings of this measure have been discussed in detail earlier. In essence, the proxies for the information shares are the coefficients or weights of the permanent component of the vector error correction process. A VECM representation such as $\Delta X_t = \gamma\beta' X_{t-1} + \sum_{i=1}^{\infty} \Gamma_i \Delta X_{t-i} + e_t$ can be decomposed into permanent and transient or stationary components as $X_t = A_1 f_t + A_2 z_t$. $A_1 f_t$ is the non stationary component where

$f_t = \gamma_{\perp}^{'} X_t$ and the component share $\mathbf{IS_i} = \frac{\alpha_{\perp,i}}{\alpha_{\perp,1}+\alpha_{\perp,2}}$.

The Gonzalo-Granger measure was estimated using a bivariate VECM, since the object of this study is not a comparison of both measures, but the effect of market changes on relative information shares. Since this approach does not require a rotation of the cointegrating vectors, and also as a variation in approach, the model was not estimated over each day. Instead, the data was pooled into a single matrix. As there is no rotation, a single estimate instead of upper and lower limits is reported. The model was estimated between the Cincinnati exchange and the NYSE. Table 7.7 shows the estimates for the bid and ask series for 1999 for the Cincinnati exchange and the NYSE. The GG measure differs considerably in its estimates from the Hasbrouck measure. It often attributes the entire information share to the NYSE, as there are several estimates where the share is 100%. This is indeed an overestimate. One reason could be in the drawbacks of the measure itself. In the comparative study of the performance of the two measures by Hasbrouck (**?**), the G&G measure had invariably incorrectly estimated the statistical parameters of the series, and even estimating the information share, it grossly underestimated the share of the one market while overestimating the share of the other (refer to case 3). Another reason could be that both the Cincinnati exchange and the NYSE lost share to the Boston exchange and the Cincinnati exchange could have lost a relatively larger share. The same trend is seen in Tables 7.8 and 7.9, which show the estimates for the series from 2000 and 2001.

### 6.2.3 Impulse Response Functions

The impulse response functions are generated from the VMA representation. They describe how a shock to one series is communicated to the other series in a cointegrated system, and how long it takes for the system to return to equilibrium. Initially, the system is in equilibrium and when a shock is imparted to one variable, it is communicated to other series due to the interlinked nature of a cointegrated system. The shock may be considered as partly transient and partly permanent. The permanent portion is incorporated into the common stochastic trend, and the transient part dies out. The values of the other series respond to the permanent component, and the system reaches a new equilibrium as innovations to the constituent series converge.

The impulse responses are successive derivatives of the VMA with respect to system time. The system is first at equilibrium and unit shock or one standard deviation shock is imparted to one variable. The future values of the changes to each variable are now estimated from the infinite VMA representation. The changes communicated via the disturbance terms and the values of the variables keep changing with each successive cycle until they converge, and the system stabilizes at a new equilibrium. This would be the effective innovation to the common stochastic trend.

In the present model, the variables are quote series from the Boston stock exchange, the Cincinnati stock exchange and the NYSE. The VMA representation of the VECM is first obtained, and then a unit impulse is delivered to each market in turn. The perturbations are now forecast with the VMA to observe the changes to the disturbance terms. A graphical representation of the impulse responses can be seen in Figures A.1, A.2, and A.3. They are a representative sample of the 450 such impulse response graphs. The top left panel of Figure A.1 shows the effect of a unit impulse to the Boston exchange bid series. The greater part of the impulse dies out very quickly within the first 10 to 60 cycles, but some effect persists for a longer time before the three series converge. It can be noticed that the other two series do not respond to any large extent to an impulse to Boston. This unit impulse can be interpreted as a quote change in Boston, and since its information contribution is minimal, it is not surprising that the other two quotes do not move much. Consequently, the new equilibrium level of efficient price has not changed by very much. The picture is very different in the case of the third panel on the left. Here a unit impulse is delivered to the NYSE quote, and the other two respond by rising rapidly, i.e., they are quickly incorporating the new information entering the system via an innovation to the NYSE quotes. Convergence occurs at a large distance from the original rest level. The system retains most of the innovation, and the new equilibrium or efficient price reflects this. Again, this is consistent with the information share of the NYSE, which contributes more than 90% of new information. The other figures are further examples of the impulse response functions.

Table 7.10 shows the estimates of the impulse responses after a unit shock is delivered to the Boston bid series from 1999. 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 a very short time. In real markets, the minimum step size for a change is the tick, i.e., if the tick is 10 cents, then all changes take place at steps of 10 or higher. Any finer granulation cannot be observed. However, in econometric analysis we can set the convergence tolerance to an arbitrarily high level. This would require more cycles before the convergence criterion is satisfied. Setting such fine tolerance levels makes it possible to measure difference in convergence times. The convergence criterion is set to about five decimal places.

Table 7.11 shows the impulse responses and convergence times after a unit impulse is delivered to the Cincinnati series from 1999, and Table 7.12 describes the effects of a unit impulse to the NYSE series. From the values, it can be seen that the impulse to Boston loses about 94-97% of its value, by the time convergence is reached, whereas Cincinnati loses about 85-90% of its value, and the NYSE impulse loses only about 10%. The results show that the impulses to Boston and Cincinnati have a relatively smaller 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 the NYSE is the dominant market where you expect informed traders to participate. Hence, any innovations in this market will have a large impact on the efficient price. This is again consistent with the information share contributions of each market. These tables report how long the the efficient price evolves before the system stabilizes. Note that these are innovations to the efficient price and as such have a permanent effect on the long run equilibrium price. This is in contrast to a VAR, where all the components are stationary, and any such shock dies out after some time.

The impulse responses from the bid series from 2000 are shown in Tables 7.13, 7.14, and 7.15 for a unit impulse to the Boston stock exchange, the Cincinnati exchange, and the NYSE respectively. This is the period when Reg. FD was implemented but decimalization was not. Consistent with Hypothesis 2b, the convergence rates do not seem to have changed much. However, in agreement with Hypothesis 2a, the level, i.e., the value at which the convergence occurs, is much higher. This shows that the dominance of the NYSE has somewhat diminished compared to 1999. This is consistent with the regional markets now contributing more to price discovery due to Reg. FD.

The results for the bid series from 2001, i.e., the period when decimalization was implemented, are shown in Tables 7.16 to 7.18. It can be immediately noticed that the time taken for convergence is very much longer than for earlier periods. This result is consistent with Hypothesis 1a. Decimalization allows markets to improve their prices in much smaller steps, and therefore convergence takes longer. The levels at which convergence takes place do not show much difference from the 2000 series, which is again consistent with the assumption that decimalization does not impact the information share of markets.

Tables 7.19 to 7.27 show the results for the three periods i.e., 1999, 2000, and 2001, for the offer series. Though investigators have found the off-NYSE offers to be more aggressive, the results are similar to the bid series.

## 6.3 Hypothesis Tests

These tests are the essence of this thesis. They test the main hypothesis and establish whether the data substantiates the premise on which this research rests.

### 6.3.1 Test of Hypotheses 1a and 2b

These hypotheses propose that *"the impulse responses will take a significantly longer time to converge after Decimalization"* and *"Impulse responses durations will not be affected by Reg. FD."*. These propositions were tested by conducting two sample t-tests of the mean convergence times for the impulse responses from the pre- and post-decimalization periods, i.e., 1999, 2000, and 2001. A cursory glance at the convergence times from Tables 7.10-7.12 (1999 bid series), 7.13-7.15 (2000 bid series), and Tables 7.16-7.18 (2001 bid series) indicates that while there is no significant change between 1999 and 2000 there is indeed a significant change between 2000 and 2001.

The results of a formal t-test of the mean convergence times between the pre-decimalization periods of 1999 and 2000 and the post-decimalization period of 2001 are tabulated in Table 7.32, 7.33, 7.34, and 7.35. The tests of Hypothesis 2b are in Tables 7.32 and 7.33 for the bid and offer series, respectively. The results are t-tests between the mean convergence times between 1999 and 2000 when decimalization was not implemented and only Reg. FD was in force. The first row shows the result of the t-test for a unit impulse to the Boston exchange from 1999 and 2000. The differences for the bid series as well as the offer series are not significant since the p-values are 0.44 and 0.95, respectively. The other two rows show the results for the Cincinnati exchange and the NYSE. Both show that there is no significant change in the convergence times with p-values of 0.3 and 0.103, respectively, for the bid series and 0.86 and 0.67, for the offer series. The last column reports the results for a test of equal variances. The results are consistent with the hypothesis.

Tables 7.34 and 7.35 show the results of the t-tests of Hypothesis 1a, corresponding to difference in mean convergence times between 2000 and 2001, for the bid and offer series. The rows as before correspond to the Boston stock exchange, the Cincinnati stock exchange and the NYSE. Here the results are dramatically different. The bid series in Table 7.34 shows impulse response convergence times take a significantly longer time to converge in the post-decimalization period i.e., 2001. The post-pre mean difference is significant, with a p-value of less than 0.0001. The results are the same for the other two markets. Table 7.35 tabulates the results for the offer series. These results are in strong support of Hypothesis 1a. Moreover, it must be noted that while there is a time interval of a full year between the data from 1999 and 2000, only three months elapsed between the data from 2000 and 2001, and the only significant event that occurred during this time is decimalization.

### 6.3.2 Test of Hypotheses 1b and 2a

**Hypothesis 1b**

The information shares that are used in these tests were estimated using the two metrics, i.e., the Hasbrouck or IS measure and the Gonzalo-Granger or G&G/PT measure. Hypotheses 1b states that *"information share of markets will not be significantly affected by decimalization."* Panel 3 of Table 7.28 tests this proposition. We see that during the period of 2000-2001 when decimalization was implemented, the mean information share did not change. The p-values for the share of the Boston exchange, the Cincinnati exchange and the NYSE are 0.37, 0.57 and 0.88, respectively. Panel 3 of Table 7.29 shows the results of the t-test for the offer series during the same period. The results are not so unambiguous here; while Cincinnati shows no difference (p-value = 0.62), Boston and NYSE do show a significant difference (p-values 0.038 and 0.027). There could be several reasons for such results; as noted earlier, investigators have documented more aggressive offer-side behavior from off-NYSE exchanges. Another reason might be that the effects of decimalization were gradual, in that all stocks were not converted at the same time.

**Hypothesis 2a**

This hypothesis states that *“differences in information shares of markets will decrease significantly after Reg. FD.”*. That is, the share of the so-called satellite or regional exchanges would increase while the share of the dominant market would decrease after implementation of Reg. FD. This is to be expected if the regulation has achieved its goal of introducing a more even playing field. Tables 7.28 and 7.29 document the tests of information share changes for the IS measure, while Tables 39 and 40 tabulate the results for the G&G/PT measure.

Panel 1 of Table 7.28 shows the tests of the Reg. FD period, i.e., 1999-2000 for the bid series. The Boston market has increased its share, and the difference is significant (p-value = 0.027,) and NYSE share has decreased significantly (p-value = 0.001). However, Cincinnati has also lost share, the decrease is significant (p-value = 0.0001). This is an unexpected result. A possible reason could be that both the NYSE and the Cincinnati exchange have lost information share to the Boston exchange. That is, some of the informed traders may have moved to Boston. The results for the offer series are documented in panel 1 of Table 7.29. Once again Boston has increased its information share whereas Cincinnati has lost its share. The result for the NYSE share is borderline significant at the 5% level. It would seem that more information share was lost by Cincinnati to Boston than to the NYSE. The reasons could be the subject for a separate investigation.

Tables 7.30 and 7.31 contain the results of tests for the G&G/PT measure of information for the bid and offer series, respectively. Panel 1 of Table 7.30 shows that the G&G measure was unable to capture any significant difference in information share during the Reg. FD period (p-value = 0.64,) but there seems to be a significant difference during the decimalization period (Table 7.30, panel 2, p-value = 0.03). The offer series in Table 7.31

shows the opposite results, with the Reg. FD period being significant at the 10% level (p-value = 0.6), and the decimalization period being insignificant (p-value = 0.55). G&G measure suffers from mis-estimation defects as demonstrated by Hasbrouck. Besides this, the estimation is over a bivariate VECM involving Cincinnati which has exhibited slightly anomalous behavior as seen also in the IS measure.The analysis should perhaps be done pairwise between all the three exchanges.

### 6.4 Impulse Response Differences Between Contemporaneous Bid-Offer

Though it is not germane to the main questions of this thesis, as a precaution, differences in convergence times of the bid and offer series were tested. The results are shown in Tables 7.36, 7.37, and 7.38. The tests show that there was no difference in the convergence times of impulse responses between bid and offer series of the same period.

# CHAPTER 7

## 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 regulations. Far from achieving any improvement, they may cause harm, which if left unnoticed 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.

If prices are to be efficient, the price formation process has to incorporate new information as quickly as possible. The quantity of information arriving in a market may not be immediately reflected in prices. Bottlenecks are created by the trading rules; for example, if the stipulated minimum change or tick is too large, small amounts of incoming information will not immediately be incorporated. Such information must be accumulated until there is a sufficient quantity to warrant a change. The widespread availability of information is another issue that influences price formation. If information is differentially distributed, i.e., participants are denied equal access to information, asymmetry is introduced. Such flaws tend to make prices inefficient. Thus price discovery is sensitive to the trading rules or structure of markets. Any regulations that affect any of these rules would in turn affect the price discovery process.

In the recent past, two such regulations have been implemented; one affecting the distribution of information, i.e., Regulation Fair Disclosure, and the other affecting the minimum mandated price change, i.e., decimalization of the tick-size. The motives underlying both these changes are laudable. Both aim to improve the efficiency of markets. But the question is whether they achieved this. There is a large body of literature on tick-size, but its verdict on informational effects is inconclusive. Regulation FD, on the other hand, has not received as much attention. The informational aspects have been studied almost exclusively from the perspective of analysts' forecast accuracy. Both these regulatory changes have the potential for significant effects on the price discovery process since, on one hand, they affect the trading mechanism, and on the other, the dissemination of information.

This study uses a rather computationally demanding methodology to investigate the informational and process effects of these two regulations. For any such effort, a reliable metric or yardstick is required. Two such measures, though econometrically intensive, seem to meet the requirements. One was developed by Joel Hasbrouck, a leading researcher in microstructure, expressly to measure the information share of markets. The other has evolved as an application of a time series analysis methodology developed the Nobel laureate Clive Granger and Jesus Gonzalo. By using these measures, the information share and response times of the markets before and after the implementation of regulations can be measured. The changes or differences in these quantities would then indicate whether these regulations have been effective or futile, or altogether undesirable.

The purpose of Regulation Fair Disclosure is to bring about a measure of equality in the market. Hitherto, firms informed a select group of persons before informing the general public. This has placed the "ordinary" trader under a considerable disadvantage. Reg. FD is quite clear in what it wished to address:

> ... Issuer selective disclosure bears a close resemblance in this regard to

> ordinary "tipping" and insider trading. In both cases, a privileged few gain an informational edge – and the ability to use that edge to profit – from their superior access to corporate insiders, rather than from their skill, acumen, or diligence. Likewise, selective disclosure has an adverse impact on market integrity that is similar to the adverse impact from illegal insider trading: investors lose confidence in the fairness of the markets when they know that other participants may exploit "unerodable informational advantages" derived not from hard work or insights, but from their access to corporate insiders…

If the regulation is successful, we should see greater parity in information distribution. This would mean that the informed traders who operate in the dominant markets would lose some of their advantage. The participants in other markets can also contribute information gained through their own "*…skill, acumen, or diligence.*" The information contributions of smaller venues should in fact increase. This is the theme that underlies the Hypothesis 2a: that after Reg. FD is implemented, the information share of smaller markets should increase or the difference between the dominant and satellite markets should decrease. 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.

However, the evidence could have been stronger. The information share of the Cincinnati exchange has shown a decrease instead of an increase as expected. The fact that Cincinnati is also a dominant market as compared to Boston could perhaps explain this result. The information shares as measured by the G&G/PT measure have not shown any evidence in support of Reg. FD. But as shown earlier, this measure was not expressly designed to measure information shares. It is more an incidental use of a method developed by someone who had a different purpose in mind. Overall, there is enough evidence to conclude that

Regulation FD has been a reasonable success, if not a resounding one.

Changes to tick-size, in this case a comparatively large reduction in the minimum step of price revision, should have a noticeable effect on the process of price formation. The informational effect would be not one of quantity. It is more likely to affect the system response to impulses, progress towards a new equilibrium, once a shock has disturbed it. Hypothesis 1a addresses this question of the time it takes for the system to fully internalize the permanent information contained in a shock and reach a new equilibrium. Since the smaller tick-size allows smaller revisions, markets need not incorporate all the change in another market at once. They could revise gradually, which would enable them to arrive at equilibrium without losing any trading advantage. A precipitate change would place some of the existing limit orders at a disadvantage, i.e., the price might trade through. A more gradual rate of change would enable the market to execute its pending orders with much smaller price shocks. This could be an inducement to traders.

The evidence in support of Hypothesis 1a very strong. All the tests, on the bid as well as the offer side, show conclusively that the impulse responses take a much longer time to converge. This means that once the existing equilibrium is disturbed, the system is taking a longer time to reach a new equilibrium. This could be interpreted as meaning that a price shock to any venue is more gradually incorporated by other venues after decimalization. Whether this is an intended consequence of decimalization or not, is a debatable issue.

## 7.1 Limitations and Future Research

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 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.

The evidence in support of Regulation Fair Disclosure is not as convincing as one would have hoped for. The anomalous behavior of Cincinnati is puzzling. It could be that there were transaction cost issues or some other factors that have introduced some obfuscation. A more comprehensive model that also incorporates such effects could be an objective of further research. It would have been highly desirable if the G&G/PT measure confirmed the results of the Hasbrouck measure. It could be a drawback of the method itself, but perhaps a greater refinement or a better algorithm would achieve better results.

The evidence on the effect of tick-size does not address the question of informational effects either directly or completely. The approach only measures the convergence speeds, i.e., the rate at which new equilibrium is reached. This is only indirect evidence of the rate at which new information in one venue is incorporated by other venues. Subsequent research should be directed towards addressing this issue directly. One approach would be to compare adjustment coefficients, since they directly measure the size of the revision to each component of the cointegrated system. However, there are no reliable tests that would allow a direct comparison of speeds-of-adjustment. As it is, there is quite a degree of complexity, which can introduce artifacts. A further complication, such as nesting or pooling the periods, may only obscure the rather small effects. Brassi, Caporale & Hall (2007) note that most of the existing methods of comparing adjustment coefficients only establish the existence of a structural break. They cannot quantify the differences in speeds-of-adjustment with sufficient accuracy to warrant any conclusions.

Overall this study has in its small way added to the evidence that exists on the efficacy of two major regulations. More importantly, it has introduced a novel use of two existing measures. Most of the previous literature has only used cointegration analysis to measure information shares, but none has used the estimates of the measures to test other phenomena.

## 7.2 Tables

Table 7.1: Information Share(IS) - Series 1999 Bid

The table contains the information share estimates of the Hasbrouck measure, for the bid series from 1999, when neither Reg. FD nor decimalization was implemented. Since there are two cointegrating vectors, the estimates from all the rotations of the vectors were aggregated to obtain a maximum and minimum estimate for each stock.The first column shows the name of the stock, and the subsequent columns show the information share estimate and the associated standard error, for the price series from the Boston, Cincinnati and New York stock exchanges.

| | Maximum Estimates | | | | | | Minimum Estimates | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Boston | | Cincinnati | | NYSE | | Boston | | Cincinnati | | NYSE | |
| Stock | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err |
| Alcoa | 0.2110 | 0.0194 | 0.2644 | 0.0288 | 0.9264 | 0.0133 | 0.0293 | 0.0113 | 0.0381 | 0.0086 | 0.6037 | 0.0272 |
| AIG | 0.2348 | 0.0132 | 0.2875 | 0.0162 | 0.9740 | 0.0043 | 0.0032 | 0.0007 | 0.0134 | 0.0031 | 0.6345 | 0.0138 |
| Am Express | 0.2536 | 0.0152 | 0.2653 | 0.0137 | 0.9806 | 0.0023 | 0.0064 | 0.0013 | 0.0087 | 0.0021 | 0.6406 | 0.0150 |
| Boeing | 0.1513 | 0.0220 | 0.2160 | 0.0163 | 0.8936 | 0.0184 | 0.0620 | 0.0164 | 0.0360 | 0.0068 | 0.6676 | 0.0237 |
| BOA | 0.0941 | 0.0110 | 0.2135 | 0.0168 | 0.9552 | 0.0068 | 0.0238 | 0.0059 | 0.0162 | 0.0032 | 0.7353 | 0.0187 |
| Citigroup | 0.1121 | 0.0132 | 0.1966 | 0.0188 | 0.9181 | 0.0131 | 0.0399 | 0.0106 | 0.0387 | 0.0074 | 0.7175 | 0.0200 |
| Caterpillar | 0.0766 | 0.0092 | 0.1957 | 0.0211 | 0.9471 | 0.0083 | 0.0228 | 0.0065 | 0.0249 | 0.0044 | 0.7554 | 0.0215 |
| Chevron | 0.1780 | 0.0134 | 0.2926 | 0.0214 | 0.9622 | 0.0058 | 0.0103 | 0.0038 | 0.0181 | 0.0041 | 0.6402 | 0.0183 |
| Du Pont | 0.1388 | 0.0121 | 0.2551 | 0.0136 | 0.9587 | 0.0054 | 0.0112 | 0.0027 | 0.0211 | 0.0044 | 0.6754 | 0.0154 |
| Disney | 0.0683 | 0.0098 | 0.1216 | 0.0113 | 0.8791 | 0.0120 | 0.0563 | 0.0092 | 0.0626 | 0.0095 | 0.8131 | 0.0128 |
| GE | 0.1876 | 0.0128 | 0.2306 | 0.0181 | 0.9578 | 0.0164 | 0.0060 | 0.0013 | 0.0318 | 0.0165 | 0.6705 | 0.0167 |
| GM | 0.1894 | 0.0183 | 0.2156 | 0.0152 | 0.9316 | 0.0151 | 0.0334 | 0.0115 | 0.0262 | 0.0065 | 0.6654 | 0.0190 |
| Home Depot | 0.0631 | 0.0102 | 0.2020 | 0.0182 | 0.9547 | 0.0083 | 0.0195 | 0.0054 | 0.0224 | 0.0072 | 0.7569 | 0.0188 |
| IBM | 0.0432 | 0.0073 | 0.1368 | 0.0122 | 0.9609 | 0.0073 | 0.0133 | 0.0053 | 0.0239 | 0.0059 | 0.8309 | 0.0126 |
| J&J | 0.1082 | 0.0154 | 0.2253 | 0.0162 | 0.9599 | 0.0059 | 0.0190 | 0.0049 | 0.0162 | 0.0036 | 0.7122 | 0.0165 |
| JP Morgan | 0.2274 | 0.0171 | 0.3107 | 0.0225 | 0.9473 | 0.0218 | 0.0077 | 0.0026 | 0.0280 | 0.0118 | 0.6102 | 0.0216 |
| Coca-Cola | 0.0077 | 0.0026 | 0.0280 | 0.0118 | 0.6102 | 0.0216 | 0.0127 | 0.0028 | 0.0283 | 0.0047 | 0.7693 | 0.0179 |
| McDonald | 0.1259 | 0.0216 | 0.2704 | 0.0209 | 0.8991 | 0.0191 | 0.0705 | 0.0192 | 0.0232 | 0.0041 | 0.6345 | 0.0241 |
| 3M | 0.2311 | 0.0143 | 0.2550 | 0.0153 | 0.9789 | 0.0040 | 0.0063 | 0.0027 | 0.0078 | 0.0018 | 0.6461 | 0.0154 |
| Merck | 0.1048 | 0.0200 | 0.1841 | 0.0170 | 0.9368 | 0.0166 | 0.0264 | 0.0165 | 0.0308 | 0.0051 | 0.7436 | 0.0237 |
| Pfizer | 0.1142 | 0.0143 | 0.1457 | 0.0210 | 0.8321 | 0.0223 | 0.0711 | 0.0138 | 0.0944 | 0.0209 | 0.7492 | 0.0205 |
| P&G | 0.1959 | 0.0143 | 0.2429 | 0.0151 | 0.9698 | 0.0052 | 0.0124 | 0.0042 | 0.0120 | 0.0026 | 0.6625 | 0.0144 |
| AT&T | 0.0496 | 0.0091 | 0.1084 | 0.0120 | 0.9256 | 0.0101 | 0.0291 | 0.0071 | 0.0430 | 0.0072 | 0.8466 | 0.0146 |
| UTX | 0.1817 | 0.0185 | 0.2491 | 0.0259 | 0.9441 | 0.0124 | 0.0246 | 0.0110 | 0.0263 | 0.0064 | 0.6442 | 0.0235 |
| Wal-Mart | 0.0514 | 0.0077 | 0.1424 | 0.0116 | 0.9537 | 0.0073 | 0.0226 | 0.0068 | 0.0211 | 0.0031 | 0.8162 | 0.0131 |

Table 7.2: Information Share(IS) - Series 1999 Offer

The table contains the information share estimates of the Hasbrouck measure, for the offer series from 1999, when neither Reg. FD nor decimalization was implemented. Since there are two cointegrating vectors, the estimates from all the rotations of the vectors were aggregated to obtain a maximum and minimum estimate for each stock.The first column shows the name of the stock, and the subsequent columns show the information share estimate and the associated standard error, for the price series from the Boston, Cincinnati and New York stock exchanges.

| | Maximum Estimates | | | | | | Minimum Estimates | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Boston | | Cincinnati | | NYSE | | Boston | | Cincinnati | | NYSE | |
| Stock | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err |
| Alcoa | 0.2047 | 0.0197 | 0.2352 | 0.0253 | 0.9360 | 0.0122 | 0.0226 | 0.007106433 | 0.0355 | 0.008158674 | 0.634 | 0.023317031 |
| AIG | 0.2071 | 0.0139 | 0.2815 | 0.0194 | 0.9739 | 0.0034 | 0.004 | 0.000899742 | 0.0118 | 0.002485727 | 0.6545 | 0.017232338 |
| Am Express | 0.2081 | 0.0158 | 0.2665 | 0.0149 | 0.9712 | 0.0055 | 0.0053 | 0.00102174 | 0.0151 | 0.004605457 | 0.6542 | 0.014365365 |
| Boeing | 0.1031 | 0.0179 | 0.1786 | 0.0171 | 0.8965 | 0.0181 | 0.0564 | 0.014868611 | 0.0429 | 0.00858567 | 0.7343 | 0.023957525 |
| BOA | 0.0878 | 0.0116 | 0.2471 | 0.0193 | 0.9478 | 0.0097 | 0.0124 | 0.003431218 | 0.0309 | 0.008677169 | 0.7056 | 0.019763815 |
| Citigroup | 0.0904 | 0.0112 | 0.2135 | 0.0160 | 0.9472 | 0.0086 | 0.0174 | 0.006511689 | 0.0308 | 0.004940954 | 0.7257 | 0.016835842 |
| Caterpillar | 0.1141 | 0.0155 | 0.1983 | 0.0181 | 0.9148 | 0.0147 | 0.0445 | 0.011300144 | 0.0354 | 0.008341672 | 0.7165 | 0.02235629 |
| Chevron | 0.1841 | 0.0181 | 0.2341 | 0.0178 | 0.9586 | 0.0144 | 0.021 | 0.012398134 | 0.013 | 0.005764446 | 0.6841 | 0.021014303 |
| Du Pont | 0.1088 | 0.0111 | 0.2577 | 0.0170 | 0.9631 | 0.0054 | 0.0067 | 0.001967232 | 0.0235 | 0.004574957 | 0.6878 | 0.017247588 |
| Disney | 0.0668 | 0.0120 | 0.1530 | 0.0135 | 0.8532 | 0.0170 | 0.0541 | 0.01069015 | 0.0902 | 0.012352384 | 0.7843 | 0.017613585 |
| GE | 0.1513 | 0.0120 | 0.2178 | 0.0118 | 0.9786 | 0.0032 | 0.0042 | 0.000823492 | 0.0127 | 0.002455227 | 0.7141 | 0.01280988 |
| GM | 0.1523 | 0.0215 | 0.2104 | 0.0177 | 0.9332 | 0.0171 | 0.0293 | 0.0159666 | 0.0314 | 0.007289432 | 0.6873 | 0.022280041 |
| Home Depot | 0.0732 | 0.0063 | 0.2218 | 0.0173 | 0.9525 | 0.0097 | 0.0157 | 0.003629466 | 0.0287 | 0.008051925 | 0.7313 | 0.017659334 |
| IBM | 0.0544 | 0.0074 | 0.1614 | 0.0113 | 0.9627 | 0.0067 | 0.0141 | 0.003598966 | 0.0207 | 0.004163211 | 0.8025 | 0.01276413 |
| J&J | 0.0952 | 0.0111 | 0.2151 | 0.0169 | 0.9614 | 0.0047 | 0.0147 | 0.003263469 | 0.0161 | 0.002866973 | 0.7313 | 0.018833573 |
| JP Morgan | 0.2457 | 0.0148 | 0.2828 | 0.0172 | 0.9637 | 0.0064 | 0.0082 | 0.001845233 | 0.0209 | 0.005520448 | 0.6185 | 0.01706459 |
| Coca-Cola | 0.0600 | 0.0088 | 0.1287 | 0.0129 | 0.9390 | 0.0083 | 0.0323 | 0.007609679 | 0.0259 | 0.00431571 | 0.8212 | 0.014472114 |
| McDonald | 0.1278 | 0.0180 | 0.2375 | 0.0192 | 0.8990 | 0.0179 | 0.0662 | 0.016668094 | 0.0284 | 0.00747243 | 0.6602 | 0.020114561 |
| 3M | 0.2308 | 0.0128 | 0.2413 | 0.0185 | 0.9726 | 0.0072 | 0.0067 | 0.001326738 | 0.0149 | 0.006145692 | 0.6538 | 0.017171339 |
| Merck | 0.0959 | 0.0119 | 0.1648 | 0.0157 | 0.9198 | 0.0145 | 0.0352 | 0.008951666 | 0.041 | 0.00849417 | 0.7597 | 0.019824814 |
| Pfizer | 0.0993 | 0.0129 | 0.1301 | 0.0109 | 0.8745 | 0.0096 | 0.0427 | 0.008173923 | 0.0804 | 0.007563929 | 0.7806 | 0.016088599 |
| P&G | 0.1947 | 0.0163 | 0.2503 | 0.0160 | 0.9676 | 0.0038 | 0.0079 | 0.002256979 | 0.0194 | 0.003110971 | 0.6617 | 0.017125589 |
| AT&T | 0.0234 | 0.0053 | 0.0835 | 0.0088 | 0.9613 | 0.0054 | 0.0093 | 0.00321772 | 0.0284 | 0.004635957 | 0.8958 | 0.009790408 |
| UTX | 0.1559 | 0.0162 | 0.2130 | 0.0273 | 0.9644 | 0.0059 | 0.0132 | 0.004574957 | 0.0157 | 0.003614216 | 0.6941 | 0.025345262 |
| Wal-Mart | 0.0736 | 0.0120 | 0.1681 | 0.0136 | 0.9361 | 0.0106 | 0.0351 | 0.008417921 | 0.0254 | 0.005794946 | 0.7742 | 0.017262838 |

Table 7.3: Information Share(IS) - Series 2000 Bid

The table contains the information share estimates of the Hasbrouck measure, for the bid series from 2000, when Reg. FD was implemented but decimalization was not. Since there are two cointegrating vectors, the estimates from all the rotations of the vectors were aggregated to obtain a maximum and minimum estimate for each stock.The first column shows the name of the stock, and the subsequent columns show the information share estimate and the associated standard error, for the price series from the Boston, Cincinnati and New York stock exchanges.

| | Maximum Estimates | | | | | | Minimum Estimates | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Boston | | Cincinnati | | NYSE | | Boston | | Cincinnati | | NYSE | |
| Stock | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err |
| Alcoa | 0.1563 | 0.0176 | 0.1055 | 0.0122 | 0.9199 | 0.0097 | 0.0346 | 0.0071 | 0.0428 | 0.0071 | 0.7556 | 0.0192 |
| AIG | 0.2796 | 0.0181 | 0.0622 | 0.0081 | 0.9753 | 0.0043 | 0.0109 | 0.0020 | 0.0084 | 0.0026 | 0.6881 | 0.0184 |
| Am Express | 0.2022 | 0.0178 | 0.0916 | 0.0100 | 0.9677 | 0.0044 | 0.0141 | 0.0028 | 0.0160 | 0.0036 | 0.7388 | 0.0182 |
| Boeing | 0.2762 | 0.0275 | 0.1149 | 0.0190 | 0.9249 | 0.0254 | 0.0353 | 0.0167 | 0.0294 | 0.0084 | 0.6542 | 0.0296 |
| BOA | 0.1304 | 0.0164 | 0.0541 | 0.0096 | 0.9548 | 0.0087 | 0.0274 | 0.0071 | 0.0162 | 0.0053 | 0.8251 | 0.0183 |
| Citigroup | 0.1176 | 0.0114 | 0.0945 | 0.0136 | 0.9659 | 0.0053 | 0.0160 | 0.0036 | 0.0164 | 0.0031 | 0.8081 | 0.0150 |
| Caterpillar | 0.1403 | 0.0128 | 0.1364 | 0.0161 | 0.9166 | 0.0163 | 0.0257 | 0.0075 | 0.0530 | 0.0121 | 0.7405 | 0.0180 |
| Chevron | 0.2526 | 0.0242 | 0.1459 | 0.0147 | 0.9292 | 0.0089 | 0.0219 | 0.0057 | 0.0455 | 0.0080 | 0.6498 | 0.0235 |
| Du Pont | 0.1653 | 0.0209 | 0.1185 | 0.0134 | 0.9320 | 0.0112 | 0.0327 | 0.0110 | 0.0323 | 0.0056 | 0.7423 | 0.0211 |
| Disney | 0.1430 | 0.0203 | 0.1063 | 0.0129 | 0.8711 | 0.0142 | 0.0653 | 0.0129 | 0.0605 | 0.0099 | 0.7601 | 0.0205 |
| GE | 0.0933 | 0.0099 | 0.0663 | 0.0085 | 0.9463 | 0.0071 | 0.0191 | 0.0039 | 0.0333 | 0.0058 | 0.8464 | 0.0141 |
| GM | 0.1124 | 0.0145 | 0.1006 | 0.0146 | 0.9331 | 0.0126 | 0.0201 | 0.0053 | 0.0451 | 0.0112 | 0.7991 | 0.0189 |
| Home Depot | 0.0621 | 0.0079 | 0.1115 | 0.0164 | 0.9357 | 0.0084 | 0.0280 | 0.0054 | 0.0351 | 0.0068 | 0.8326 | 0.0184 |
| IBM | 0.0773 | 0.0076 | 0.0344 | 0.0040 | 0.9875 | 0.0018 | 0.0070 | 0.0013 | 0.0047 | 0.0013 | 0.8952 | 0.0082 |
| J&J | 0.1845 | 0.0185 | 0.1481 | 0.0162 | 0.9575 | 0.0066 | 0.0157 | 0.0039 | 0.0238 | 0.0055 | 0.7114 | 0.0201 |
| JP Morgan | 0.4907 | 0.0199 | 0.1597 | 0.0102 | 0.9837 | 0.0027 | 0.0070 | 0.0016 | 0.0035 | 0.0011 | 0.4866 | 0.0182 |
| Coca-Cola | 0.1646 | 0.0169 | 0.1103 | 0.0128 | 0.9600 | 0.0077 | 0.0197 | 0.0045 | 0.0179 | 0.0053 | 0.7534 | 0.0174 |
| McDonald | 0.1559 | 0.0183 | 0.0972 | 0.0144 | 0.8674 | 0.0192 | 0.0594 | 0.0160 | 0.0710 | 0.0120 | 0.7514 | 0.0239 |
| 3M | 0.4399 | 0.0185 | 0.0767 | 0.0073 | 0.9739 | 0.0044 | 0.0130 | 0.0030 | 0.0068 | 0.0025 | 0.5383 | 0.0189 |
| Merck | 0.2812 | 0.0193 | 0.0958 | 0.0099 | 0.9640 | 0.0061 | 0.0134 | 0.0030 | 0.0205 | 0.0052 | 0.6643 | 0.0206 |
| Pfizer | 0.1105 | 0.0166 | 0.0605 | 0.0096 | 0.9178 | 0.0118 | 0.0389 | 0.0106 | 0.0422 | 0.0080 | 0.8327 | 0.0176 |
| P&G | 0.2122 | 0.0205 | 0.0851 | 0.0094 | 0.9509 | 0.0061 | 0.0169 | 0.0035 | 0.0294 | 0.0051 | 0.7292 | 0.0202 |
| AT&T | 0.0836 | 0.0139 | 0.0873 | 0.0075 | 0.8727 | 0.0120 | 0.0617 | 0.0118 | 0.0635 | 0.0062 | 0.8318 | 0.0133 |
| UTX | 0.3322 | 0.0258 | 0.1113 | 0.0092 | 0.9623 | 0.0060 | 0.0157 | 0.0039 | 0.0188 | 0.0037 | 0.6162 | 0.0258 |
| Wal-Mart | 0.1329 | 0.0170 | 0.0663 | 0.0084 | 0.9489 | 0.0090 | 0.0288 | 0.0076 | 0.0207 | 0.0044 | 0.8109 | 0.0170 |

Table 7.4: Information Share(IS) - Series 2000 Offer

The table contains the information share estimates of the Hasbrouck measure, for the offer series from 2000, when Reg. FD was implemented but decimalization was not. Since there are two cointegrating vectors, the estimates from all the rotations of the vectors were aggregated to obtain a maximum and minimum estimate for each stock.The first column shows the name of the stock, and the subsequent columns show the information share estimate and the associated standard error, for the price series from the Boston, Cincinnati and New York stock exchanges.

| | Maximum Estimates | | | | | | Minimum Estimates | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Boston | | Cincinnati | | NYSE | | Boston | | Cincinnati | | NYSE | |
| Stock | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err |
| Alcoa | 0.1595 | 0.0222 | 0.1401 | 0.0241 | 0.8597 | 0.0226 | 0.0599 | 0.0157 | 0.0778 | 0.0194 | 0.7150 | 0.0283 |
| AIG | 0.2550 | 0.0209 | 0.0772 | 0.0071 | 0.9762 | 0.0038 | 0.0062 | 0.0014 | 0.0126 | 0.0032 | 0.7006 | 0.0185 |
| Am Express | 0.2395 | 0.0237 | 0.1052 | 0.0115 | 0.9608 | 0.0058 | 0.0161 | 0.0039 | 0.0209 | 0.0047 | 0.6951 | 0.0229 |
| Boeing | 0.1587 | 0.0179 | 0.0749 | 0.0105 | 0.9629 | 0.0073 | 0.0157 | 0.0044 | 0.0193 | 0.0050 | 0.7833 | 0.0180 |
| BOA | 0.1594 | 0.0215 | 0.0566 | 0.0121 | 0.9461 | 0.0097 | 0.0368 | 0.0087 | 0.0135 | 0.0045 | 0.7951 | 0.0230 |
| Citigroup | 0.1274 | 0.0171 | 0.1045 | 0.0166 | 0.9549 | 0.0087 | 0.0232 | 0.0066 | 0.0184 | 0.0042 | 0.7883 | 0.0222 |
| Caterpillar | 0.1057 | 0.0175 | 0.0947 | 0.0137 | 0.8937 | 0.0217 | 0.0584 | 0.0178 | 0.0453 | 0.0108 | 0.8043 | 0.0218 |
| Chevron | 0.2409 | 0.0217 | 0.1241 | 0.0115 | 0.9412 | 0.0104 | 0.0225 | 0.0054 | 0.0321 | 0.0069 | 0.6803 | 0.0216 |
| Du Pont | 0.1272 | 0.0150 | 0.1118 | 0.0122 | 0.9383 | 0.0091 | 0.0218 | 0.0053 | 0.0375 | 0.0071 | 0.7780 | 0.0193 |
| Disney | 0.1300 | 0.0197 | 0.0812 | 0.0087 | 0.9052 | 0.0173 | 0.0539 | 0.0166 | 0.0381 | 0.0060 | 0.7979 | 0.0210 |
| GE | 0.1089 | 0.0156 | 0.0603 | 0.0072 | 0.9409 | 0.0106 | 0.0256 | 0.0086 | 0.0320 | 0.0057 | 0.8359 | 0.0163 |
| GM | 0.1397 | 0.0166 | 0.0874 | 0.0118 | 0.9382 | 0.0136 | 0.0314 | 0.0116 | 0.0285 | 0.0080 | 0.7860 | 0.0169 |
| Home Depot | 0.0637 | 0.0106 | 0.0957 | 0.0185 | 0.9461 | 0.0109 | 0.0265 | 0.0062 | 0.0256 | 0.0083 | 0.8455 | 0.0202 |
| IBM | 0.0956 | 0.0097 | 0.0410 | 0.0062 | 0.9804 | 0.0040 | 0.0098 | 0.0017 | 0.0087 | 0.0027 | 0.8729 | 0.0122 |
| J&J | 0.1341 | 0.0141 | 0.1282 | 0.0152 | 0.9497 | 0.0100 | 0.0186 | 0.0047 | 0.0283 | 0.0082 | 0.7713 | 0.0187 |
| JP Morgan | 0.4762 | 0.0179 | 0.1786 | 0.0110 | 0.9882 | 0.0016 | 0.0051 | 0.0010 | 0.0032 | 0.0012 | 0.5019 | 0.0165 |
| Coca-Cola | 0.0950 | 0.0134 | 0.0653 | 0.0088 | 0.9461 | 0.0105 | 0.0280 | 0.0094 | 0.0243 | 0.0055 | 0.8485 | 0.0152 |
| McDonald | 0.1472 | 0.0181 | 0.1036 | 0.0187 | 0.8353 | 0.0225 | 0.0844 | 0.0162 | 0.0783 | 0.0173 | 0.7543 | 0.0233 |
| 3M | 0.3834 | 0.0179 | 0.0666 | 0.0102 | 0.9775 | 0.0036 | 0.0056 | 0.0013 | 0.0114 | 0.0034 | 0.5858 | 0.0170 |
| Merck | 0.1499 | 0.0179 | 0.0483 | 0.0058 | 0.9677 | 0.0064 | 0.0193 | 0.0048 | 0.0114 | 0.0026 | 0.8130 | 0.0191 |
| Pfizer | 0.0880 | 0.0100 | 0.0613 | 0.0075 | 0.9142 | 0.0106 | 0.0391 | 0.0075 | 0.0447 | 0.0072 | 0.8543 | 0.0130 |
| P&G | 0.1828 | 0.0202 | 0.0502 | 0.0075 | 0.9524 | 0.0088 | 0.0253 | 0.0081 | 0.0207 | 0.0053 | 0.7771 | 0.0183 |
| AT&T | 0.0489 | 0.0064 | 0.1067 | 0.0104 | 0.8839 | 0.0112 | 0.0358 | 0.0058 | 0.0789 | 0.0096 | 0.8466 | 0.0118 |
| UTX | 0.2943 | 0.0197 | 0.1106 | 0.0112 | 0.9533 | 0.0093 | 0.0228 | 0.0056 | 0.0218 | 0.0053 | 0.6441 | 0.0213 |
| Wal-Mart | 0.0988 | 0.0140 | 0.0788 | 0.0116 | 0.9405 | 0.0095 | 0.0272 | 0.0065 | 0.0288 | 0.0054 | 0.8331 | 0.0183 |

Table 7.5: Information Share(IS) - Series 2001 Bid

The table contains the information share estimates of the Hasbrouck measure, for the bid series from 2001, when both Reg. FD and decimalization were in force. Since there are two cointegrating vectors, the estimates from all the rotations of the vectors were aggregated to obtain a maximum and minimum estimate for each stock.The first column shows the name of the stock, and the subsequent columns show the information share estimate and the associated standard error, for the price series from the Boston, Cincinnati and New York stock exchanges.

| | Maximum Estimates | | | | | | Minimum Estimates | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Boston | | Cincinnati | | NYSE | | Boston | | Cincinnati | | NYSE | |
| Stock | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err |
| Alcoa | 0.2475 | 0.0385 | 0.0879 | 0.0188 | 0.8714 | 0.0276 | 0.0799 | 0.0238 | 0.0434 | 0.0147 | 0.6828 | 0.0395 |
| AIG | 0.4210 | 0.0424 | 0.0566 | 0.0069 | 0.9379 | 0.0206 | 0.0509 | 0.0207 | 0.0077 | 0.0025 | 0.5527 | 0.0405 |
| Am Express | 0.2514 | 0.0348 | 0.0566 | 0.0068 | 0.9112 | 0.0183 | 0.0698 | 0.0181 | 0.0169 | 0.0037 | 0.7011 | 0.0322 |
| Boeing | 0.1836 | 0.0308 | 0.1141 | 0.0129 | 0.9405 | 0.0182 | 0.0331 | 0.0172 | 0.0227 | 0.0046 | 0.7293 | 0.0309 |
| BOA | 0.2644 | 0.0385 | 0.0925 | 0.0205 | 0.9330 | 0.0238 | 0.0386 | 0.0110 | 0.0219 | 0.0163 | 0.6800 | 0.0398 |
| Citigroup | 0.1511 | 0.0271 | 0.0841 | 0.0109 | 0.9140 | 0.0163 | 0.0527 | 0.0160 | 0.0317 | 0.0070 | 0.7731 | 0.0255 |
| Caterpillar | 0.2339 | 0.0273 | 0.0870 | 0.0122 | 0.9166 | 0.0135 | 0.0547 | 0.0119 | 0.0246 | 0.0059 | 0.6981 | 0.0264 |
| Chevron | 0.3267 | 0.0325 | 0.0858 | 0.0090 | 0.9537 | 0.0087 | 0.0295 | 0.0075 | 0.0123 | 0.0037 | 0.6344 | 0.0315 |
| Du Pont | 0.1332 | 0.0225 | 0.0744 | 0.0114 | 0.9247 | 0.0148 | 0.0548 | 0.0140 | 0.0179 | 0.0062 | 0.8023 | 0.0226 |
| Disney | 0.1626 | 0.0227 | 0.0951 | 0.0106 | 0.8476 | 0.0206 | 0.0991 | 0.0184 | 0.0491 | 0.0077 | 0.7503 | 0.0253 |
| GE | 0.0334 | 0.0047 | 0.0598 | 0.0064 | 0.9568 | 0.0060 | 0.0167 | 0.0037 | 0.0257 | 0.0042 | 0.9087 | 0.0078 |
| GM | 0.1608 | 0.0237 | 0.0886 | 0.0148 | 0.9490 | 0.0126 | 0.0216 | 0.0053 | 0.0234 | 0.0108 | 0.7732 | 0.0276 |
| Home Depot | 0.0537 | 0.0090 | 0.0495 | 0.0067 | 0.9706 | 0.0064 | 0.0184 | 0.0056 | 0.0100 | 0.0032 | 0.9022 | 0.0112 |
| IBM | 0.0657 | 0.0112 | 0.1295 | 0.0229 | 0.9287 | 0.0231 | 0.0337 | 0.0076 | 0.0361 | 0.0224 | 0.8115 | 0.0245 |
| J&J | 0.0950 | 0.0171 | 0.0917 | 0.0139 | 0.9215 | 0.0167 | 0.0516 | 0.0158 | 0.0258 | 0.0073 | 0.8190 | 0.0198 |
| JP Morgan | 0.1482 | 0.0240 | 0.0769 | 0.0251 | 0.9039 | 0.0272 | 0.0516 | 0.0111 | 0.0411 | 0.0219 | 0.7842 | 0.0328 |
| Coca-Cola | 0.1139 | 0.0210 | 0.0895 | 0.0142 | 0.8977 | 0.0174 | 0.0598 | 0.0142 | 0.0405 | 0.0097 | 0.8037 | 0.0229 |
| McDonald | 0.2489 | 0.0374 | 0.1080 | 0.0242 | 0.7938 | 0.0339 | 0.1285 | 0.0290 | 0.0743 | 0.0228 | 0.6510 | 0.0389 |
| 3M | 0.5496 | 0.0251 | 0.2112 | 0.0165 | 0.9681 | 0.0058 | 0.0105 | 0.0027 | 0.0131 | 0.0030 | 0.4197 | 0.0244 |
| Merck | 0.0911 | 0.0134 | 0.0780 | 0.0137 | 0.9348 | 0.0105 | 0.0301 | 0.0069 | 0.0318 | 0.0075 | 0.8382 | 0.0187 |
| Pfizer | 0.1117 | 0.0194 | 0.0819 | 0.0202 | 0.8746 | 0.0254 | 0.0694 | 0.0125 | 0.0536 | 0.0193 | 0.8102 | 0.0290 |
| P&G | 0.3813 | 0.0394 | 0.0960 | 0.0124 | 0.9553 | 0.0121 | 0.0259 | 0.0091 | 0.0123 | 0.0051 | 0.5712 | 0.0368 |
| AT&T | 0.0926 | 0.0182 | 0.0751 | 0.0138 | 0.8729 | 0.0191 | 0.0730 | 0.0164 | 0.0519 | 0.0113 | 0.8351 | 0.0210 |
| UTX | 0.3015 | 0.0328 | 0.1190 | 0.0177 | 0.9166 | 0.0222 | 0.0407 | 0.0105 | 0.0356 | 0.0116 | 0.6267 | 0.0346 |
| Wal-Mart | 0.1337 | 0.0275 | 0.0858 | 0.0140 | 0.9432 | 0.0107 | 0.0312 | 0.0068 | 0.0236 | 0.0084 | 0.7959 | 0.0286 |

Table 7.6: Information Share(IS) - Series 2001 Offer

The table contains the information share estimates of the Hasbrouck measure, for the offer series from 2001, when both Reg. FD and decimalization were in force. Since there are two cointegrating vectors, the estimates from all the rotations of the vectors were aggregated to obtain a maximum and minimum estimate for each stock.The first column shows the name of the stock, and the subsequent columns show the information share estimate and the associated standard error, for the price series from the Boston, Cincinnati and New York stock exchanges.

| | Maximum Estimates | | | | | | Minimum Estimates | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Boston | | Cincinnati | | NYSE | | Boston | | Cincinnati | | NYSE | |
| Stock | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err | IS | Std Err |
| Alcoa | 0.1969 | 0.0281 | 0.1271 | 0.0187 | 0.8924 | 0.0235 | 0.0498 | 0.0142 | 0.0536 | 0.0137 | 0.7004 | 0.0332 |
| AIG | 0.4612 | 0.0352 | 0.0659 | 0.0093 | 0.9330 | 0.0161 | 0.0517 | 0.0159 | 0.0091 | 0.0024 | 0.5107 | 0.0343 |
| Am Express | 0.2957 | 0.0398 | 0.0934 | 0.0117 | 0.9130 | 0.0228 | 0.0611 | 0.0221 | 0.0219 | 0.0063 | 0.6483 | 0.0377 |
| Boeing | 0.3184 | 0.0381 | 0.1413 | 0.0146 | 0.9196 | 0.0212 | 0.0578 | 0.0211 | 0.0196 | 0.0044 | 0.5984 | 0.0325 |
| BOA | 0.1450 | 0.0148 | 0.1239 | 0.0259 | 0.9102 | 0.0275 | 0.0416 | 0.0094 | 0.0440 | 0.0238 | 0.7543 | 0.0283 |
| Citigroup | 0.1656 | 0.0259 | 0.0893 | 0.0097 | 0.9399 | 0.0085 | 0.0321 | 0.0060 | 0.0259 | 0.0063 | 0.7632 | 0.0246 |
| Caterpillar | 0.1538 | 0.0243 | 0.1075 | 0.0146 | 0.9170 | 0.0128 | 0.0436 | 0.0096 | 0.0333 | 0.0080 | 0.7555 | 0.0256 |
| Chevron | 0.3788 | 0.0409 | 0.0924 | 0.0093 | 0.9668 | 0.0050 | 0.0239 | 0.0047 | 0.0055 | 0.0018 | 0.5915 | 0.0385 |
| Du Pont | 0.1873 | 0.0300 | 0.0716 | 0.0106 | 0.9142 | 0.0201 | 0.0662 | 0.0203 | 0.0168 | 0.0051 | 0.7568 | 0.0281 |
| Disney | 0.1327 | 0.0270 | 0.0872 | 0.0127 | 0.8833 | 0.0225 | 0.0771 | 0.0213 | 0.0379 | 0.0085 | 0.7847 | 0.0281 |
| GE | 0.0717 | 0.0107 | 0.0668 | 0.0098 | 0.9359 | 0.0127 | 0.0301 | 0.0076 | 0.0325 | 0.0078 | 0.8652 | 0.0162 |
| GM | 0.2474 | 0.0382 | 0.0962 | 0.0131 | 0.9234 | 0.0198 | 0.0573 | 0.0186 | 0.0147 | 0.0054 | 0.6927 | 0.0365 |
| Home Depot | 0.0960 | 0.0147 | 0.0783 | 0.0126 | 0.9453 | 0.0133 | 0.0372 | 0.0092 | 0.0166 | 0.0084 | 0.8340 | 0.0180 |
| IBM | 0.0665 | 0.0094 | 0.1123 | 0.0098 | 0.9586 | 0.0084 | 0.0293 | 0.0069 | 0.0110 | 0.0037 | 0.8301 | 0.0130 |
| J&J | 0.1021 | 0.0147 | 0.0910 | 0.0121 | 0.9264 | 0.0108 | 0.0485 | 0.0102 | 0.0224 | 0.0057 | 0.8171 | 0.0164 |
| JP Morgan | 0.2326 | 0.0388 | 0.0677 | 0.0107 | 0.9340 | 0.0163 | 0.0427 | 0.0142 | 0.0203 | 0.0065 | 0.7170 | 0.0389 |
| Coca-Cola | 0.1421 | 0.0320 | 0.0663 | 0.0119 | 0.8530 | 0.0300 | 0.1142 | 0.0307 | 0.0311 | 0.0079 | 0.7950 | 0.0313 |
| McDonald | 0.2202 | 0.0398 | 0.1261 | 0.0220 | 0.7756 | 0.0374 | 0.1416 | 0.0347 | 0.0794 | 0.0168 | 0.6622 | 0.0403 |
| 3M | 0.5979 | 0.0234 | 0.2137 | 0.0127 | 0.9586 | 0.0097 | 0.0213 | 0.0039 | 0.0074 | 0.0029 | 0.3786 | 0.0204 |
| Merck | 0.1289 | 0.0214 | 0.0692 | 0.0086 | 0.9351 | 0.0117 | 0.0406 | 0.0116 | 0.0221 | 0.0043 | 0.8108 | 0.0208 |
| Pfizer | 0.0752 | 0.0114 | 0.0708 | 0.0103 | 0.9192 | 0.0141 | 0.0420 | 0.0101 | 0.0369 | 0.0074 | 0.8570 | 0.0156 |
| P&G | 0.3084 | 0.0374 | 0.0936 | 0.0117 | 0.9140 | 0.0243 | 0.0586 | 0.0246 | 0.0254 | 0.0056 | 0.6311 | 0.0354 |
| AT&T | 0.1176 | 0.0198 | 0.0534 | 0.0110 | 0.8879 | 0.0167 | 0.0711 | 0.0132 | 0.0394 | 0.0101 | 0.8311 | 0.0225 |
| UTX | 0.4037 | 0.0395 | 0.1818 | 0.0275 | 0.9364 | 0.0100 | 0.0262 | 0.0056 | 0.0282 | 0.0075 | 0.5179 | 0.0376 |
| Wal-Mart | 0.1269 | 0.0198 | 0.0918 | 0.0118 | 0.9381 | 0.0097 | 0.0306 | 0.0061 | 0.0293 | 0.0077 | 0.7969 | 0.0216 |

Table 7.7: Information Share(PT/GG) Estimates - Series 1999

The table contains the information share estimates of the PT/GG measure, for the Cincinnati and NYSE bid and offer series from 1999, when both Reg. FD and decimalization were not implemented.

| | Cincinnati | | NYSE | |
|---|---|---|---|---|
| Stock | Bid | Offer | Bid | Offer |
| Alcoa | 0.00412 | 0.00524 | 0.99588 | 0.99476 |
| AIG | 0.00010 | 0.00000 | 0.99990 | 1.00000 |
| Am Express | 0.00000 | 0.00000 | 1.00000 | 1.00000 |
| Boeing | 0.00073 | 0.00000 | 0.99927 | 1.00000 |
| BOA | 0.00824 | 0.00000 | 0.99176 | 1.00000 |
| Citigroup | 0.01615 | 0.00000 | 0.98385 | 1.00000 |
| Caterpillar | 0.00000 | 0.00347 | 1.00000 | 0.99653 |
| Chevron | 0.00000 | 0.00143 | 1.00000 | 0.99857 |
| Du Pont | 0.00256 | 0.00182 | 0.99744 | 0.99818 |
| Disney | 0.06159 | 0.04206 | 0.93841 | 0.95794 |
| GE | 0.00180 | 0.00296 | 0.99820 | 0.99704 |
| GM | 0.00000 | 0.00964 | 1.00000 | 0.99036 |
| Home Depot | 0.00534 | 0.00145 | 0.99466 | 0.99855 |
| IBM | 0.00000 | 0.00225 | 1.00000 | 0.99775 |
| J&J | 0.00504 | 0.02228 | 0.99496 | 0.97772 |
| JP Morgan | 0.67197 | 0.00745 | 0.32803 | 0.99255 |
| Coca-Cola | 0.00000 | 0.00000 | 1.00000 | 1.00000 |
| McDonald | 0.00000 | 0.00000 | 1.00000 | 1.00000 |
| 3M | 0.00000 | 0.00654 | 1.00000 | 0.99346 |
| Merck | 0.00000 | 0.01053 | 1.00000 | 0.98947 |
| Pfizer | 0.00000 | 0.00080 | 1.00000 | 0.99920 |
| P&G | 0.00316 | 0.01042 | 0.99684 | 0.98958 |
| AT&T | 0.00000 | 0.00365 | 1.00000 | 0.99635 |
| UTX | 0.00000 | 0.00963 | 1.00000 | 0.99037 |
| Wal-Mart | 0.00571 | 0.00052 | 0.99429 | 0.99948 |

Table 7.8: Information Share(PT/GG) Estimates - Series 2000

The table contains the information share estimates of the PT/GG measure, for the Cincinnati and NYSE bid and offer series from 2000, when Reg. FD was implemented.

| | Cincinnati | | NYSE | |
|---|---|---|---|---|
| Stock | Bid | Offer | Bid | Offer |
| Alcoa | 0.009938 | 0.020822 | 0.990062 | 0.979179 |
| AIG | 0.059958 | 0.039789 | 0.940043 | 0.960211 |
| Am Express | 0.000000 | 0.008233 | 1.000000 | 0.991767 |
| Boeing | 0.038908 | 0.000000 | 0.961093 | 1.000000 |
| BOA | 0.015835 | 0.000629 | 0.984165 | 0.999371 |
| Citigroup | 0.001609 | 0.007348 | 0.998391 | 0.992652 |
| Caterpillar | 0.000000 | 0.001135 | 1.000000 | 0.998865 |
| Chevron | 0.028557 | 0.002442 | 0.971443 | 0.997558 |
| Du Pont | 0.024064 | 0.009453 | 0.975936 | 0.990547 |
| Disney | 0.087908 | 0.027140 | 0.912092 | 0.972860 |
| GE | 0.055394 | 0.018461 | 0.944606 | 0.981539 |
| GM | 0.000507 | 0.006040 | 0.999493 | 0.993960 |
| Home Depot | 0.034036 | 0.000000 | 0.965964 | 1.000000 |
| IBM | 0.010756 | 0.019564 | 0.989244 | 0.980436 |
| J&J | 0.000690 | 0.002900 | 0.999310 | 0.997100 |
| JP Morgan | 0.000000 | 0.008300 | 1.000000 | 0.991700 |
| Coca-Cola | 0.000000 | 0.007843 | 1.000000 | 0.992157 |
| McDonald | 0.027613 | 0.012343 | 0.972387 | 0.987657 |
| 3M | 0.000000 | 0.003640 | 1.000000 | 0.996360 |
| Merck | 0.000000 | 0.000000 | 1.000000 | 1.000000 |
| Pfizer | 0.054870 | 0.099192 | 0.945130 | 0.900808 |
| P&G | 0.000000 | 0.028288 | 1.000000 | 0.971713 |
| AT&T | 0.005405 | 0.000000 | 0.994595 | 1.000000 |
| UTX | 0.002060 | 0.000000 | 0.997940 | 1.000000 |
| Wal-Mart | 0.008008 | 0.047519 | 0.991992 | 0.952481 |

Table 7.9: Information Share(PT/GG) Estimates - Series 2001

The table contains the information share estimates of the PT/GG measure, for the Cincinnati and NYSE bid and offer series from 2001, when decimalization was implemented.

| | Cincinnati | | NYSE | |
|---|---|---|---|---|
| Stock | Bid | Offer | Bid | Offer |
| Alcoa | 0.067387 | 0.010907 | 0.932613 | 0.989093 |
| AIG | 0.000000 | 0.000000 | 1.000000 | 1.000000 |
| Am Express | 0.095653 | 0.024179 | 0.904347 | 0.975822 |
| Boeing | 0.000000 | 0.019687 | 1.000000 | 0.980313 |
| BOA | 0.184145 | 0.005418 | 0.815856 | 0.994582 |
| Citigroup | 0.060786 | 0.000000 | 0.939214 | 1.000000 |
| Caterpillar | 0.021963 | 0.016417 | 0.978037 | 0.983583 |
| Chevron | 0.000000 | 0.000000 | 1.000000 | 1.000000 |
| Du Pont | 0.040532 | 0.000000 | 0.959468 | 1.000000 |
| Disney | 0.000000 | 0.000000 | 1.000000 | 1.000000 |
| GE | 0.013303 | 0.004704 | 0.986698 | 0.995296 |
| GM | 0.009966 | 0.002127 | 0.990035 | 0.997873 |
| Home Depot | 0.000000 | 0.016957 | 1.000000 | 0.983043 |
| IBM | 0.171836 | 0.000000 | 0.828164 | 1.000000 |
| J&J | 0.040206 | 0.038534 | 0.959794 | 0.961466 |
| JP Morgan | 0.378080 | 0.000000 | 0.621920 | 1.000000 |
| Coca-Cola | 0.036379 | 0.049197 | 0.963621 | 0.950803 |
| McDonald | 0.000000 | 0.011956 | 1.000000 | 0.988044 |
| 3M | 0.026932 | 0.003003 | 0.973068 | 0.996997 |
| Merck | 0.017416 | 0.001120 | 0.982584 | 0.998880 |
| Pfizer | 0.157017 | 0.000000 | 0.842983 | 1.000000 |
| P&G | 0.000000 | 0.270315 | 1.000000 | 0.729685 |
| AT&T | 0.000000 | 0.050559 | 1.000000 | 0.949441 |
| UTX | 0.349162 | 0.019087 | 0.650838 | 0.980914 |
| Wal-Mart | 0.019544 | 0.000000 | 0.980456 | 1.000000 |

Table 7.10: Impulse Responses. Series 1999 Bid.

The table contains the convergence results after a unit impulse was imparted to the Boston bid seriesfrom 1999. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to Boston | | | | |
|---|---|---|---|---|
| Alcoa | 0.0656 | 0.0656 | 0.0655 | 1835 |
| AIG | 0.0611 | 0.0611 | 0.0611 | 1146 |
| Am Express | 0.0892 | 0.0892 | 0.0892 | 1428 |
| Boeing | 0.0993 | 0.0689 | 0.0684 | 2000 |
| BOA | 0.0103 | 0.0102 | 0.0102 | 1963 |
| Citigroup | 0.0495 | 0.0498 | 0.0498 | 1909 |
| Caterpillar | 0.0530 | 0.0539 | 0.0540 | 1879 |
| Chevron | 0.0134 | 0.0134 | 0.0134 | 1662 |
| Du Pont | 0.0835 | 0.0835 | 0.0835 | 788 |
| Disney | 0.0429 | 0.0429 | 0.0429 | 1806 |
| GE | 0.0368 | 0.0368 | 0.0368 | 811 |
| GM | 0.0228 | 0.0259 | 0.0258 | 2000 |
| Home Depot | 0.0442 | 0.0473 | 0.0473 | 1375 |
| IBM | 0.0784 | 0.0784 | 0.0784 | 1081 |
| J&J | 0.0050 | 0.0051 | 0.0051 | 1867 |
| JP Morgan | 0.0846 | 0.0846 | 0.0846 | 1638 |
| Coca-Cola | 0.0556 | 0.0557 | 0.0557 | 1573 |
| McDonald | 0.2515 | 0.2504 | 0.2504 | 1675 |
| 3M | 0.0128 | 0.0128 | 0.0128 | 832 |
| Merck | 0.0976 | 0.0977 | 0.0977 | 1636 |
| Pfizer | 0.0489 | 0.0489 | 0.0489 | 1236 |
| P&G | 0.0688 | 0.0688 | 0.0688 | 893 |
| AT&T | 0.0691 | 0.0691 | 0.0691 | 1524 |
| UTX | 0.0456 | 0.0461 | 0.0461 | 1725 |
| Wal-Mart | 0.0070 | 0.0068 | 0.0068 | 1769 |

Table 7.11: Impulse Responses. Series 1999 Bid.

The table contains the convergence results after a unit impulse was imparted to the Cincinnati bid series from 1999. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to Cincinnati | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.5181 | 0.5181 | 0.5180 | 1786 |
| AIG | 0.0521 | 0.0521 | 0.0521 | 1268 |
| Am Express | 0.1898 | 0.1898 | 0.1898 | 1394 |
| Boeing | 0.2932 | 0.2968 | 0.2969 | 2000 |
| BOA | 0.3023 | 0.3023 | 0.3023 | 1912 |
| Citigroup | 0.2317 | 0.2316 | 0.2317 | 1996 |
| Caterpillar | 0.2526 | 0.2530 | 0.2531 | 1824 |
| Chevron | 0.0049 | 0.0049 | 0.0049 | 1800 |
| Du Pont | 0.0805 | 0.0805 | 0.0805 | 799 |
| Disney | 0.0829 | 0.0829 | 0.0829 | 1946 |
| GE | 0.0910 | 0.0910 | 0.0910 | 774 |
| GM | 0.1070 | 0.1069 | 0.1069 | 2000 |
| Home Depot | 0.2170 | 0.2174 | 0.2174 | 1657 |
| IBM | 0.0788 | 0.0788 | 0.0788 | 842 |
| J&J | 0.1635 | 0.1634 | 0.1634 | 1577 |
| JP Morgan | 0.2285 | 0.2285 | 0.2285 | 1599 |
| Coca-Cola | 0.1421 | 0.1422 | 0.1422 | 1605 |
| McDonald | 0.0624 | 0.0624 | 0.0624 | 1730 |
| 3M | 0.0703 | 0.0703 | 0.0703 | 768 |
| Merck | 0.2022 | 0.2023 | 0.2022 | 1667 |
| Pfizer | 0.1528 | 0.1528 | 0.1528 | 1279 |
| P&G | 0.0747 | 0.0747 | 0.0747 | 946 |
| AT&T | 0.1446 | 0.1446 | 0.1446 | 1677 |
| UTX | 0.3010 | 0.3009 | 0.3009 | 1830 |
| Wal-Mart | 0.1501 | 0.1501 | 0.1501 | 1827 |

Table 7.12: Impulse Responses. Series 1999 Bid.

The table contains the convergence results after a unit impulse was imparted to the NYSE bid series from 1999. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to NYSE | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.4887 | 0.4887 | 0.4888 | 1688 |
| AIG | 1.0295 | 1.0295 | 1.0295 | 1003 |
| Am Express | 1.0308 | 1.0308 | 1.0308 | 1298 |
| Boeing | 0.7440 | 0.7623 | 0.7626 | 2000 |
| BOA | 0.7239 | 0.7240 | 0.7240 | 1840 |
| Citigroup | 0.8330 | 0.8334 | 0.8334 | 1803 |
| Caterpillar | 0.7888 | 0.7890 | 0.7890 | 1922 |
| Chevron | 1.0471 | 1.0471 | 1.0471 | 1452 |
| Du Pont | 0.9093 | 0.9093 | 0.9093 | 630 |
| Disney | 0.7261 | 0.7261 | 0.7261 | 1872 |
| GE | 0.8257 | 0.8257 | 0.8257 | 479 |
| GM | 0.8139 | 0.8159 | 0.8158 | 1989 |
| Home Depot | 0.8660 | 0.8666 | 0.8666 | 1453 |
| IBM | 1.0216 | 1.0216 | 1.0216 | 947 |
| J&J | 0.9300 | 0.9304 | 0.9304 | 1562 |
| JP Morgan | 0.8798 | 0.8798 | 0.8798 | 1624 |
| Coca-Cola | 0.8651 | 0.8651 | 0.8651 | 1627 |
| McDonald | 0.7414 | 0.7422 | 0.7422 | 1686 |
| 3M | 1.2417 | 1.2417 | 1.2417 | 610 |
| Merck | 0.8169 | 0.8168 | 0.8168 | 1614 |
| Pfizer | 0.9032 | 0.9032 | 0.9032 | 1141 |
| P&G | 0.9601 | 0.9601 | 0.9601 | 642 |
| AT&T | 1.0302 | 1.0303 | 1.0303 | 1478 |
| UTX | 0.7873 | 0.7877 | 0.7878 | 1779 |
| Wal-Mart | 0.8870 | 0.8871 | 0.8871 | 1811 |

Table 7.13: Impulse Responses. Series 2000 Bid.

The table contains the convergence results after a unit impulse was imparted to the Boston bid series from 2000. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to Boston | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.034 | 0.033 | 0.033 | 1852 |
| AIG | 0.002 | 0.002 | 0.002 | 1305 |
| Am Express | 0.107 | 0.107 | 0.107 | 1388 |
| Boeing | 0.153 | 0.153 | 0.153 | 1442 |
| BOA | 0.005 | 0.009 | 0.006 | 1978 |
| Citigroup | 0.114 | 0.114 | 0.114 | 1531 |
| Caterpillar | 0.015 | 0.012 | 0.012 | 2000 |
| Chevron | 0.351 | 0.349 | 0.350 | 1997 |
| Du Pont | 0.021 | 0.021 | 0.021 | 1749 |
| Disney | 0.010 | 0.010 | 0.010 | 1995 |
| GE | 0.062 | 0.062 | 0.062 | 1976 |
| GM | 0.033 | 0.033 | 0.033 | 1732 |
| Home Depot | 0.042 | 0.042 | 0.042 | 1557 |
| IBM | 0.060 | 0.060 | 0.060 | 899 |
| J&J | 0.048 | 0.048 | 0.048 | 1597 |
| JP Morgan | 0.105 | 0.105 | 0.105 | 844 |
| Coca-Cola | 0.309 | 0.309 | 0.309 | 1924 |
| McDonald | 0.400 | 0.387 | 0.381 | 1990 |
| 3M | 0.020 | 0.020 | 0.020 | 1374 |
| Merck | 0.012 | 0.012 | 0.012 | 1200 |
| Pfizer | 0.026 | 0.026 | 0.026 | 1749 |
| P&G | 0.060 | 0.059 | 0.060 | 1577 |
| AT&T | 0.120 | 0.120 | 0.120 | 1239 |
| UTX | 0.136 | 0.136 | 0.136 | 1760 |
| Wal-Mart | 0.021 | 0.021 | 0.021 | 1421 |

Table 7.14: Impulse Responses. Series 2000 Bid.

The table contains the convergence results after a unit impulse was imparted to the Cincinnati bid series from 2000. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to Cincinnati | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.183 | 0.183 | 0.183 | 1966 |
| AIG | 0.085 | 0.085 | 0.085 | 1381 |
| Am Express | 0.050 | 0.050 | 0.050 | 1600 |
| Boeing | 0.153 | 0.153 | 0.153 | 1533 |
| BOA | 0.122 | 0.106 | 0.118 | 2000 |
| Citigroup | 0.143 | 0.142 | 0.143 | 1747 |
| Caterpillar | 0.203 | 0.205 | 0.205 | 1970 |
| Chevron | 0.104 | 0.103 | 0.103 | 1967 |
| Du Pont | 0.200 | 0.200 | 0.200 | 1983 |
| Disney | 0.055 | 0.055 | 0.053 | 1995 |
| GE | 0.084 | 0.084 | 0.084 | 1601 |
| GM | 0.098 | 0.107 | 0.099 | 1984 |
| Home Depot | 0.020 | 0.020 | 0.020 | 1763 |
| IBM | 0.080 | 0.080 | 0.080 | 846 |
| J&J | 0.002 | 0.003 | 0.002 | 1314 |
| JP Morgan | 0.087 | 0.087 | 0.087 | 862 |
| Coca-Cola | 0.132 | 0.132 | 0.132 | 1905 |
| McDonald | 0.061 | 0.070 | 0.069 | 1995 |
| 3M | 0.279 | 0.282 | 0.279 | 1506 |
| Merck | 0.253 | 0.253 | 0.253 | 1107 |
| Pfizer | 0.045 | 0.045 | 0.045 | 1789 |
| P&G | 0.281 | 0.281 | 0.281 | 1792 |
| AT&T | 0.036 | 0.036 | 0.036 | 1423 |
| UTX | 0.035 | 0.035 | 0.035 | 1754 |
| Wal-Mart | 0.069 | 0.069 | 0.069 | 1533 |

Table 7.15: Impulse Responses. Series 2000 Bid.

The table contains the convergence results after a unit impulse was imparted to the NYSE bid series from 2000. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to NYSE | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Stock | Boston | Cincinnati | Nyse | Period |
| Alcoa | 0.703 | 0.702 | 0.703 | 1930 |
| AIG | 1.012 | 1.012 | 1.012 | 1435 |
| Am Express | 1.062 | 1.062 | 1.062 | 1814 |
| Boeing | 0.957 | 0.957 | 0.957 | 1510 |
| BOA | 1.000 | 0.989 | 0.997 | 1995 |
| Citigroup | 1.296 | 1.296 | 1.296 | 1848 |
| Caterpillar | 0.652 | 0.652 | 0.653 | 1997 |
| Chevron | 0.644 | 0.646 | 0.646 | 1991 |
| Du Pont | 0.793 | 0.793 | 0.793 | 1966 |
| Disney | 0.879 | 0.879 | 0.881 | 1994 |
| GE | 0.951 | 0.951 | 0.951 | 1909 |
| GM | 0.884 | 0.872 | 0.884 | 1813 |
| Home Depot | 0.877 | 0.877 | 0.877 | 1526 |
| IBM | 1.237 | 1.237 | 1.237 | 881 |
| J&J | 1.012 | 1.012 | 1.012 | 1294 |
| JP Morgan | 0.985 | 0.985 | 0.985 | 625 |
| Coca-Cola | 0.847 | 0.847 | 0.847 | 1875 |
| McDonald | 0.316 | 0.318 | 0.326 | 1976 |
| 3M | 0.684 | 0.682 | 0.684 | 1608 |
| Merck | 0.811 | 0.811 | 0.811 | 1205 |
| Pfizer | 0.903 | 0.902 | 0.903 | 1625 |
| P&G | 0.768 | 0.768 | 0.769 | 1569 |
| AT&T | 0.968 | 0.968 | 0.968 | 1233 |
| UTX | 1.180 | 1.180 | 1.180 | 1667 |
| Wal-Mart | 0.910 | 0.910 | 0.910 | 1604 |

Table 7.16: Impulse Responses. Series 2001 Bid.

The table contains the convergence results after a unit impulse was imparted to the Boston bid series from 2001. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to Boston | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.019 | 0.019 | 0.019 | 3750 |
| AIG | 0.051 | 0.051 | 0.051 | 3330 |
| Am Express | 0.275 | 0.275 | 0.275 | 3965 |
| Boeing | 0.047 | 0.047 | 0.047 | 2839 |
| BOA | 0.058 | 0.058 | 0.058 | 3419 |
| Citigroup | 0.023 | 0.024 | 0.025 | 2714 |
| Caterpillar | 0.114 | 0.114 | 0.115 | 3471 |
| Chevron | 0.059 | 0.059 | 0.059 | 1505 |
| Du Pont | 0.250 | 0.139 | 0.136 | 3886 |
| Disney | 0.101 | 0.130 | 0.141 | 3680 |
| GE | 0.078 | 0.079 | 0.079 | 1840 |
| GM | 0.063 | 0.063 | 0.063 | 3794 |
| Home Depot | 0.064 | 0.064 | 0.064 | 2219 |
| IBM | 0.038 | 0.038 | 0.038 | 2079 |
| J&J | 0.002 | 0.002 | 0.002 | 3788 |
| JP Morgan | 0.179 | 0.179 | 0.179 | 2474 |
| Coca-Cola | 0.077 | 0.077 | 0.077 | 3537 |
| McDonald | 0.316 | 0.306 | 0.300 | 2955 |
| 3M | 0.064 | 0.064 | 0.064 | 2463 |
| Merck | 0.189 | 0.189 | 0.189 | 2872 |
| Pfizer | 0.081 | 0.080 | 0.079 | 3788 |
| P&G | 0.058 | 0.048 | 0.048 | 3928 |
| AT&T | 0.010 | 0.002 | 0.001 | 3394 |
| UTX | 0.052 | 0.052 | 0.052 | 2049 |
| Wal-Mart | 0.019 | 0.019 | 0.019 | 2793 |

Table 7.17: Impulse Responses. Series 2001 Bid.

The table contains the convergence results after a unit impulse was imparted to the Cincinnati bid series from 2001. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to Cincinnati | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.260 | 0.260 | 0.260 | 3604 |
| AIG | 0.039 | 0.039 | 0.039 | 3630 |
| Am Express | 0.086 | 0.086 | 0.086 | 3702 |
| Boeing | 0.050 | 0.050 | 0.050 | 1826 |
| BOA | 0.215 | 0.215 | 0.215 | 2788 |
| Citigroup | 0.011 | 0.010 | 0.010 | 2382 |
| Caterpillar | 0.002 | 0.006 | 0.002 | 2379 |
| Chevron | 0.044 | 0.044 | 0.044 | 1674 |
| Du Pont | 0.451 | 0.433 | 0.433 | 3190 |
| Disney | 0.054 | 0.060 | 0.062 | 3738 |
| GE | 0.095 | 0.095 | 0.095 | 2544 |
| GM | 0.065 | 0.066 | 0.065 | 3664 |
| Home Depot | 0.003 | 0.003 | 0.003 | 2096 |
| IBM | 0.015 | 0.015 | 0.015 | 1785 |
| J&J | 0.063 | 0.063 | 0.063 | 2448 |
| JP Morgan | 0.078 | 0.078 | 0.078 | 2352 |
| Coca-Cola | 0.135 | 0.135 | 0.135 | 3369 |
| McDonald | 0.150 | 0.148 | 0.146 | 3468 |
| 3M | 0.001 | 0.001 | 0.001 | 2426 |
| Merck | 0.008 | 0.008 | 0.008 | 2557 |
| Pfizer | 0.064 | 0.064 | 0.064 | 3761 |
| P&G | 0.046 | 0.062 | 0.061 | 3909 |
| AT&T | 0.126 | 0.154 | 0.147 | 3818 |
| UTX | 0.003 | 0.003 | 0.003 | 2288 |
| Wal-Mart | 0.029 | 0.028 | 0.028 | 1914 |

Table 7.18: Impulse Responses. Series 2001 Bid.

The table contains the convergence results after a unit impulse was imparted to the NYSE bid series from 2001. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to NYSE | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.629 | 0.629 | 0.629 | 3722 |
| AIG | 1.013 | 1.013 | 1.013 | 2813 |
| Am Express | 0.817 | 0.818 | 0.818 | 3637 |
| Boeing | 1.140 | 1.140 | 1.140 | 2965 |
| BOA | 1.191 | 1.191 | 1.191 | 3489 |
| Citigroup | 1.019 | 1.019 | 1.019 | 3738 |
| Caterpillar | 1.067 | 1.067 | 1.068 | 3794 |
| Chevron | 0.974 | 0.974 | 0.974 | 1293 |
| Du Pont | 1.193 | 1.317 | 1.320 | 3843 |
| Disney | 1.171 | 1.206 | 1.219 | 3661 |
| GE | 1.359 | 1.359 | 1.359 | 2167 |
| GM | 0.979 | 0.979 | 0.979 | 3023 |
| Home Depot | 1.164 | 1.164 | 1.164 | 2226 |
| IBM | 1.103 | 1.103 | 1.103 | 1913 |
| J&J | 0.906 | 0.906 | 0.906 | 2120 |
| JP Morgan | 0.988 | 0.988 | 0.988 | 3451 |
| Coca-Cola | 0.971 | 0.971 | 0.971 | 3488 |
| McDonald | 0.500 | 0.508 | 0.513 | 3265 |
| 3M | 1.038 | 1.038 | 1.038 | 2057 |
| Merck | 0.727 | 0.727 | 0.727 | 2689 |
| Pfizer | 1.038 | 1.039 | 1.040 | 3693 |
| P&G | 0.868 | 0.860 | 0.860 | 3697 |
| AT&T | 0.106 | 0.159 | 0.145 | 3247 |
| UTX | 1.045 | 1.045 | 1.045 | 1749 |
| Wal-Mart | 1.132 | 1.132 | 1.132 | 2402 |

Table 7.19: Impulse Responses. Series 1999 Offer.

The table contains the convergence results after a unit impulse was imparted to the Boston offer series 1999. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to Boston | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.0611 | 0.0611 | 0.0611 | 1846 |
| AIG | 0.0618 | 0.0618 | 0.0618 | 1209 |
| Am Express | 0.1514 | 0.1514 | 0.1514 | 1495 |
| Boeing | 0.0919 | 0.0920 | 0.0920 | 1842 |
| BOA | 0.0634 | 0.0634 | 0.0634 | 1817 |
| Citigroup | 0.1238 | 0.1150 | 0.1169 | 2000 |
| Caterpillar | 0.1270 | 0.1281 | 0.1272 | 1999 |
| Chevron | 0.0047 | 0.0047 | 0.0047 | 1193 |
| Du Pont | 0.0440 | 0.0440 | 0.0440 | 1777 |
| Disney | 0.0439 | 0.0439 | 0.0439 | 1870 |
| GE | 0.0251 | 0.0251 | 0.0251 | 1317 |
| GM | 0.2494 | 0.2507 | 0.2507 | 1952 |
| Home Depot | 0.0283 | 0.0218 | 0.0218 | 1865 |
| IBM | 0.0279 | 0.0279 | 0.0280 | 1168 |
| J&J | 0.1015 | 0.1023 | 0.1024 | 1678 |
| JP Morgan | 0.0720 | 0.0720 | 0.0720 | 866 |
| Coca-Cola | 0.0400 | 0.0353 | 0.0345 | 1486 |
| McDonald | 0.0070 | 0.0064 | 0.0064 | 1615 |
| 3M | 0.1041 | 0.1041 | 0.1041 | 660 |
| Merck | 0.0182 | 0.0183 | 0.0183 | 1837 |
| Pfizer | 0.1259 | 0.1259 | 0.1259 | 1938 |
| P&G | 0.0147 | 0.0147 | 0.0147 | 1311 |
| AT&T | 0.0390 | 0.0390 | 0.0390 | 1961 |
| UTX | 0.0020 | 0.0017 | 0.0016 | 1793 |
| Wal-Mart | 0.0260 | 0.0261 | 0.0261 | 1672 |

Table 7.20: Impulse Responses. Series 1999 Offer.

The table contains the convergence results after a unit impulse was imparted to the Cincinnati offer series from 1999. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to Cincinnati | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.0438 | 0.0438 | 0.0438 | 2000 |
| AIG | 0.0996 | 0.0996 | 0.0996 | 1216 |
| Am Express | 0.3090 | 0.3090 | 0.3090 | 1294 |
| Boeing | 0.1336 | 0.1336 | 0.1336 | 1714 |
| BOA | 0.0281 | 0.0281 | 0.0281 | 1913 |
| Citigroup | 0.1289 | 0.1208 | 0.1230 | 2000 |
| Caterpillar | 0.0248 | 0.0379 | 0.0276 | 2000 |
| Chevron | 0.1683 | 0.1683 | 0.1683 | 1022 |
| Du Pont | 0.0035 | 0.0035 | 0.0035 | 1761 |
| Disney | 0.2976 | 0.2976 | 0.2976 | 1894 |
| GE | 0.0788 | 0.0788 | 0.0788 | 1285 |
| GM | 0.0214 | 0.0215 | 0.0215 | 1959 |
| Home Depot | 0.1527 | 0.1518 | 0.1518 | 1892 |
| IBM | 0.1001 | 0.1001 | 0.1001 | 1244 |
| J&J | 0.0426 | 0.0426 | 0.0426 | 1877 |
| JP Morgan | 0.3121 | 0.3121 | 0.3121 | 775 |
| Coca-Cola | 0.0710 | 0.0717 | 0.0718 | 1451 |
| McDonald | 0.1243 | 0.1245 | 0.1245 | 1653 |
| 3M | 0.2755 | 0.2755 | 0.2755 | 694 |
| Merck | 0.1834 | 0.1834 | 0.1834 | 1755 |
| Pfizer | 0.1823 | 0.1823 | 0.1823 | 1804 |
| P&G | 0.2018 | 0.2018 | 0.2018 | 1162 |
| AT&T | 0.1301 | 0.1301 | 0.1301 | 1878 |
| UTX | 0.2297 | 0.2296 | 0.2296 | 1958 |
| Wal-Mart | 0.2238 | 0.2238 | 0.2238 | 1676 |

Table 7.21: Impulse Responses. Series 1999 Offer.

The table contains the convergence results after a unit impulse was imparted to the NYSE offer series from 1999. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to NYSE | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.7774 | 0.7774 | 0.7774 | 1819 |
| AIG | 1.0156 | 1.0156 | 1.0156 | 1039 |
| Am Express | 1.0133 | 1.0133 | 1.0133 | 1286 |
| Boeing | 0.8273 | 0.8273 | 0.8273 | 1964 |
| BOA | 0.8688 | 0.8688 | 0.8688 | 1758 |
| Citigroup | 0.9880 | 0.9868 | 0.9874 | 2000 |
| Caterpillar | 1.0116 | 1.0017 | 1.0095 | 2000 |
| Chevron | 1.0110 | 1.0110 | 1.0110 | 797 |
| Du Pont | 1.1240 | 1.1240 | 1.1240 | 1603 |
| Disney | 0.6635 | 0.6635 | 0.6635 | 1882 |
| GE | 0.9199 | 0.9199 | 0.9199 | 905 |
| GM | 1.0250 | 1.0260 | 1.0260 | 1897 |
| Home Depot | 0.8300 | 0.8358 | 0.8358 | 1806 |
| IBM | 0.9422 | 0.9422 | 0.9422 | 1365 |
| J&J | 1.0919 | 1.0922 | 1.0922 | 1796 |
| JP Morgan | 0.7784 | 0.7784 | 0.7784 | 639 |
| Coca-Cola | 0.9370 | 0.9386 | 0.9389 | 1783 |
| McDonald | 0.8835 | 0.8836 | 0.8836 | 1827 |
| 3M | 1.0725 | 1.0725 | 1.0725 | 631 |
| Merck | 0.8525 | 0.8525 | 0.8525 | 1826 |
| Pfizer | 0.9648 | 0.9648 | 0.9648 | 1861 |
| P&G | 0.8414 | 0.8414 | 0.8414 | 1004 |
| AT&T | 1.0920 | 1.0920 | 1.0920 | 1964 |
| UTX | 1.2804 | 1.2805 | 1.2805 | 1816 |
| Wal-Mart | 0.7940 | 0.7941 | 0.7941 | 1552 |

Table 7.22: Impulse Responses. Series 2000 Offer.

The table contains the convergence results after a unit impulse was imparted to the Boston offer series from 2000. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to Boston | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.0178 | 0.0198 | 0.0177 | 1961 |
| AIG | 0.0007 | 0.0020 | 0.0012 | 1324 |
| Am Express | 0.0469 | 0.0460 | 0.0464 | 1862 |
| Boeing | 0.0207 | 0.0207 | 0.0207 | 1517 |
| BOA | 0.0033 | 0.0040 | 0.0036 | 1764 |
| Citigroup | 0.0109 | 0.0109 | 0.0109 | 1707 |
| Caterpillar | 0.1209 | 0.1086 | 0.1098 | 2000 |
| Chevron | 0.1740 | 0.1741 | 0.1742 | 1922 |
| Du Pont | 0.1600 | 0.1526 | 0.1539 | 1875 |
| Disney | 0.2277 | 0.2045 | 0.2040 | 1679 |
| GE | 0.0380 | 0.0383 | 0.0382 | 1404 |
| GM | 0.0700 | 0.0690 | 0.0699 | 1565 |
| Home Depot | 0.0231 | 0.0230 | 0.0240 | 1461 |
| IBM | 0.0536 | 0.0536 | 0.0536 | 1404 |
| J&J | 0.1678 | 0.1674 | 0.1670 | 1368 |
| JP Morgan | 0.2179 | 0.2179 | 0.2179 | 621 |
| Coca-Cola | 0.0620 | 0.0626 | 0.0630 | 1766 |
| McDonald | 0.0208 | 0.0188 | 0.0051 | 2000 |
| 3M | 0.0134 | 0.0140 | 0.0133 | 1456 |
| Merck | 0.0058 | 0.0058 | 0.0057 | 1194 |
| Pfizer | 0.0991 | 0.0991 | 0.0991 | 1543 |
| P&G | 0.0657 | 0.0658 | 0.0658 | 1868 |
| AT&T | 0.0329 | 0.0330 | 0.0330 | 1514 |
| UTX | 0.1936 | 0.1937 | 0.1937 | 1888 |
| Wal-Mart | 0.0796 | 0.0796 | 0.0797 | 1643 |

Table 7.23: Impulse Responses. Series 2000 Offer.

The table contains the convergence results after a unit impulse was imparted to the Cincinnati offer series from 2000. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to Cincinnati | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.4814 | 0.4850 | 0.4788 | 1996 |
| AIG | 0.1760 | 0.1782 | 0.1768 | 1439 |
| Am Express | 0.0119 | 0.0065 | 0.0094 | 1339 |
| Boeing | 0.0143 | 0.0143 | 0.0143 | 1418 |
| BOA | 0.2318 | 0.2300 | 0.2311 | 1948 |
| Citigroup | 0.0177 | 0.0177 | 0.0177 | 1595 |
| Caterpillar | 0.1186 | 0.1230 | 0.1225 | 2000 |
| Chevron | 0.1678 | 0.1678 | 0.1677 | 1745 |
| Du Pont | 0.0466 | 0.0516 | 0.0507 | 1420 |
| Disney | 0.1300 | 0.1377 | 0.1375 | 1629 |
| GE | 0.0180 | 0.0180 | 0.0180 | 1547 |
| GM | 0.0666 | 0.0751 | 0.0672 | 1763 |
| Home Depot | 0.0035 | 0.0038 | 0.0003 | 1186 |
| IBM | 0.0679 | 0.0679 | 0.0679 | 1335 |
| J&J | 0.1175 | 0.1180 | 0.1174 | 1501 |
| JP Morgan | 0.0905 | 0.0905 | 0.0905 | 800 |
| Coca-Cola | 0.0919 | 0.0918 | 0.0918 | 1787 |
| McDonald | 0.0782 | 0.1545 | 0.1234 | 2000 |
| 3M | 0.3201 | 0.3234 | 0.3200 | 1608 |
| Merck | 0.0720 | 0.0721 | 0.0720 | 1425 |
| Pfizer | 0.1319 | 0.1319 | 0.1319 | 1326 |
| P&G | 0.2290 | 0.2292 | 0.2293 | 1647 |
| AT&T | 0.0903 | 0.0903 | 0.0904 | 1386 |
| UTX | 0.0118 | 0.0120 | 0.0119 | 1573 |
| Wal-Mart | 0.0260 | 0.0265 | 0.0262 | 1533 |

Table 7.24: Impulse Responses. Series 2000 Offer.

The table contains the convergence results after a unit impulse was imparted to the NYSE offer series from 2000. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to NYSE | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.3662 | 0.3643 | 0.3686 | 1991 |
| AIG | 0.9281 | 0.9258 | 0.9272 | 1328 |
| Am Express | 0.9976 | 0.9975 | 0.9975 | 1504 |
| Boeing | 1.0632 | 1.0632 | 1.0632 | 1474 |
| BOA | 1.1978 | 1.1960 | 1.1971 | 1882 |
| Citigroup | 1.0909 | 1.0909 | 1.0909 | 1529 |
| Caterpillar | 0.7346 | 0.7441 | 0.7433 | 2000 |
| Chevron | 0.9630 | 0.9634 | 0.9639 | 1557 |
| Du Pont | 0.7710 | 0.7813 | 0.7795 | 1665 |
| Disney | 0.6357 | 0.6442 | 0.6445 | 1816 |
| GE | 1.0515 | 1.0516 | 1.0516 | 1526 |
| GM | 0.9876 | 0.9790 | 0.9870 | 1644 |
| Home Depot | 0.9800 | 0.9800 | 0.9803 | 1922 |
| IBM | 1.0795 | 1.0795 | 1.0795 | 1449 |
| J&J | 0.7994 | 0.7990 | 0.7999 | 1452 |
| JP Morgan | 0.9405 | 0.9405 | 0.9405 | 667 |
| Coca-Cola | 0.9370 | 0.9376 | 0.9381 | 1731 |
| McDonald | 0.7725 | 0.7190 | 0.7415 | 2000 |
| 3M | 0.6947 | 0.6900 | 0.6949 | 1444 |
| Merck | 0.9073 | 0.9070 | 0.9074 | 1340 |
| Pfizer | 0.7396 | 0.7396 | 0.7396 | 1525 |
| P&G | 0.8687 | 0.8686 | 0.8686 | 1563 |
| AT&T | 1.0898 | 1.0899 | 1.0899 | 1427 |
| UTX | 1.2411 | 1.2411 | 1.2412 | 1603 |
| Wal-Mart | 0.9609 | 0.9608 | 0.9609 | 1895 |

Table 7.25: Impulse Responses. Series 2001 Offer.

The table contains the convergence results after a unit impulse was imparted to the Boston offer series from 2001. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to Boston | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.0349 | 0.0349 | 0.0349 | 3736 |
| AIG | 0.0730 | 0.0730 | 0.0730 | 3634 |
| Am Express | 0.0500 | 0.0496 | 0.0496 | 2756 |
| Boeing | 0.0699 | 0.0699 | 0.0699 | 917 |
| BOA | 0.0798 | 0.0798 | 0.0798 | 3032 |
| Citigroup | 0.1123 | 0.1123 | 0.1124 | 2542 |
| Caterpillar | 0.0501 | 0.0502 | 0.0503 | 3708 |
| Chevron | 0.2018 | 0.1996 | 0.2000 | 3122 |
| Du Pont | 0.0277 | 0.0265 | 0.0266 | 3635 |
| Disney | 0.0012 | 0.0011 | 0.0010 | 3523 |
| GE | 0.0896 | 0.0896 | 0.0896 | 2574 |
| GM | 0.2773 | 0.2763 | 0.2760 | 2515 |
| Home Depot | 0.0352 | 0.0352 | 0.0352 | 2576 |
| IBM | 0.0674 | 0.0674 | 0.0674 | 1903 |
| J&J | 0.0766 | 0.0763 | 0.0764 | 2995 |
| JP Morgan | 0.0300 | 0.0193 | 0.0198 | 3749 |
| Coca-Cola | 0.0021 | 0.0022 | 0.0021 | 2703 |
| McDonald | 0.4836 | 0.4000 | 0.3822 | 3206 |
| 3M | 0.3100 | 0.3100 | 0.3100 | 1055 |
| Merck | 0.0766 | 0.0766 | 0.0766 | 2446 |
| Pfizer | 0.0111 | 0.0111 | 0.0111 | 2487 |
| P&G | 1.0492 | 0.0932 | 0.0601 | 3051 |
| AT&T | 0.0209 | 0.0337 | 0.0300 | 3648 |
| UTX | 0.1486 | 0.1486 | 0.1486 | 2330 |
| Wal-Mart | 0.0177 | 0.0178 | 0.0178 | 2373 |

Table 7.26: Impulse Responses. Series 2001 Offer.

The table contains the convergence results after a unit impulse was imparted to the Cincinnati offer series from 2001. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to Cincinnati | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.0342 | 0.0342 | 0.0342 | 3473 |
| AIG | 0.0534 | 0.0534 | 0.0534 | 2553 |
| Am Express | 0.0709 | 0.0710 | 0.0710 | 3103 |
| Boeing | 0.0160 | 0.0160 | 0.0160 | 967 |
| BOA | 0.1084 | 0.1084 | 0.1084 | 2432 |
| Citigroup | 0.0482 | 0.0482 | 0.0482 | 3193 |
| Caterpillar | 0.1103 | 0.1103 | 0.1103 | 3615 |
| Chevron | 0.0740 | 0.0746 | 0.0745 | 3168 |
| Du Pont | 0.0713 | 0.0712 | 0.0713 | 3935 |
| Disney | 0.0349 | 0.0349 | 0.0349 | 2412 |
| GE | 0.1684 | 0.1684 | 0.1684 | 2274 |
| GM | 0.0590 | 0.0589 | 0.0589 | 2785 |
| Home Depot | 0.0449 | 0.0449 | 0.0449 | 2460 |
| IBM | 0.0706 | 0.0706 | 0.0706 | 1814 |
| J&J | 0.0659 | 0.0661 | 0.0660 | 2705 |
| JP Morgan | 0.0290 | 0.0272 | 0.0273 | 3288 |
| Coca-Cola | 0.3073 | 0.3074 | 0.3072 | 2962 |
| McDonald | 0.0462 | 0.0426 | 0.0420 | 3230 |
| 3M | 0.1781 | 0.1781 | 0.1781 | 1127 |
| Merck | 0.0723 | 0.0723 | 0.0723 | 2209 |
| Pfizer | 0.0080 | 0.0085 | 0.0085 | 2365 |
| P&G | 0.1901 | 0.1031 | 0.0946 | 2601 |
| AT&T | 0.4000 | 0.4040 | 0.4025 | 3532 |
| UTX | 0.2767 | 0.2768 | 0.2767 | 1904 |
| Wal-Mart | 0.1924 | 0.1924 | 0.1924 | 2798 |

Table 7.27: Impulse Responses. Series 2001 Offer.

The table contains the convergence results after a unit impulse was imparted to the NYSE offer series from 2001. The first column describes the stock and the next three columns give the value at which convergence occurred. The last column shows the number of units of time elapsed for convergence to be achieved.

| Unit Impulse to NYSE | | | | |
|---|---|---|---|---|
| Stock | Boston | Cincinnati | NYSE | Period |
| Alcoa | 0.9813 | 0.9813 | 0.9813 | 3689 |
| AIG | 1.0335 | 1.0335 | 1.0335 | 3007 |
| Am Express | 0.9250 | 0.9251 | 0.9251 | 2774 |
| Boeing | 1.1312 | 1.1312 | 1.1312 | 653 |
| BOA | 0.8500 | 0.8501 | 0.8501 | 2650 |
| Citigroup | 1.0585 | 1.0585 | 1.0585 | 3007 |
| Caterpillar | 0.9247 | 0.9249 | 0.9249 | 3589 |
| Chevron | 0.8160 | 0.8171 | 0.8169 | 3206 |
| Du Pont | 1.1891 | 1.1901 | 1.1900 | 3611 |
| Disney | 1.0762 | 1.0763 | 1.0763 | 3166 |
| GE | 1.1356 | 1.1356 | 1.1356 | 2913 |
| GM | 0.7600 | 0.7623 | 0.7630 | 2040 |
| Home Depot | 1.0857 | 1.0857 | 1.0857 | 2490 |
| IBM | 0.9582 | 0.9582 | 0.9582 | 1550 |
| J&J | 0.8652 | 0.8662 | 0.8659 | 2530 |
| JP Morgan | 0.9700 | 0.9888 | 0.9879 | 3333 |
| Coca-Cola | 0.6811 | 0.6800 | 0.6815 | 2084 |
| McDonald | 0.4317 | 0.5167 | 0.5349 | 3568 |
| 3M | 0.9411 | 0.9411 | 0.9411 | 918 |
| Merck | 1.0348 | 1.0348 | 1.0348 | 2136 |
| Pfizer | 0.9558 | 0.9557 | 0.9557 | 2910 |
| P&G | 0.4936 | 0.7988 | 0.7900 | 2047 |
| AT&T | 0.6160 | 0.6232 | 0.6216 | 3542 |
| UTX | 0.6861 | 0.6860 | 0.6861 | 1927 |
| Wal-Mart | 0.9158 | 0.9159 | 0.9159 | 1981 |

Table 7.28: Information Share Tests. IS Measure - Series Bid

(a) Panel 1: Regulation FD: 1999-2000 IS Bid

The table shows the results of t-tests of differences in information shares, for the bid series. The estimates are derived with the Hasbrouck measure, before and after Reg. FD and decimalization were implemented for the three exchanges. Pre refers to the aggregate information before the regulation was implemented and Post is the aggregate information share after the regulation was in force. Panel 1 shows the results of the difference in mean information shares before and and after Reg. FD was implemented. Panel 2 shows the results of the same test for the difference between 1999 and 2001, i.e., before and after both regulations were in force. Panel 3 shows the results of the t-test before and after decimalization was implemented.

| Exchange | Mean | | Difference | P-Value | Variance |
|---|---|---|---|---|---|
| | Pre | Post | Post-Pre | | P-Value |
| Boston | 0.0808 | 0.1089 | 0.02810 | 0.0276 | 0.0402 |
| Cincinnati | 0.1194 | 0.0640 | -0.05540 | <.0001 | 0.0379 |
| NYSE | 0.8160 | 0.7385 | -0.07750 | 0.0010 | 0.0003 |

(b) Panel 2: Regulation FD: 1999-2001 IS Bid

| Exchange | Mean | | Difference | P-Value | Variance |
|---|---|---|---|---|---|
| | Pre | Post | Post-Pre | | P-Value |
| Boston | 0.0808 | 0.1236 | 0.04290 | 0.0049 | 0.0030 |
| Cincinnati | 0.1194 | 0.0604 | -0.05890 | <.0001 | 0.0136 |
| NYSE | 0.8160 | 0.7342 | -0.08180 | 0.0022 | <.0001 |

(c) Panel 3: Decimalization: 2000-2001 IS Bid

| Exchange | Mean | | Difference | P-Value | Variance |
|---|---|---|---|---|---|
| | Pre | Post | Post-Pre | | P-Value |
| Boston | 0.0808 | 0.1089 | 0.02810 | 0.0276 | 0.0402 |
| Cincinnati | 0.1194 | 0.0640 | -0.05540 | <.0001 | 0.0379 |
| NYSE | 0.8160 | 0.7385 | -0.07750 | 0.0010 | 0.0003 |

Table 7.29: Information Share Tests: IS Measure: Series Offer

(a) Panel 1: Regulation FD: 1999-2000 IS Offer

The table shows the results of t-tests of differences in information shares, for the offer series. The estimates are derived with the Hasbrouck measure, before and after Reg. FD and decimalization were implemented for the three exchanges. Pre refers to the aggregate information before the regulation was implemented and Post is the aggregate information share after the regulation was in force. Panel 1 shows the results of the difference in mean information shares before and and after Reg. FD was implemented. Panel 2 shows the results of the same test for the difference between 1999 and 2001, i.e., before and after both regulations were in force. Panel 3 shows the results of the t-test before and after decimalization was implemented.

| Exchange | Mean | | Difference | P-Value | Variance |
|---|---|---|---|---|---|
| | Pre | Post | Post-Pre | | P-Value |
| Boston | 0.0758 | 0.0986 | 0.02280 | 0.0430 | 0.0216 |
| Cincinnati | 0.1186 | 0.0603 | -0.05830 | <.0001 | 0.9170 |
| NYSE | 0.8512 | 0.8303 | -0.02090 | 0.0594 | 0.1403 |

(b) Panel 2: Regulation FD: 1999-2001 IS Offer

| Exchange | Mean | | Difference | P-Value | Variance |
|---|---|---|---|---|---|
| | Pre | Post | Post-Pre | | P-Value |
| Boston | 0.0758 | 0.1334 | 0.05760 | 0.0004 | 0.0001 |
| Cincinnati | 0.1186 | 0.0633 | -0.05540 | <.0001 | 0.7475 |
| NYSE | 0.8303 | 0.8166 | -0.0137 | 0.3361 | 0.0017 |

(c) Panel 3: Decimalization: 2000-2001 IS Offer

| Exchange | Mean | | Difference | P-Value | Variance |
|---|---|---|---|---|---|
| | Pre | Post | Post-Pre | | P-Value |
| Boston | 0.0986 | 0.1334 | 0.03480 | 0.0382 | 0.0818 |
| Cincinnati | 0.0603 | 0.0633 | 0.00296 | 0.6218 | 0.8276 |
| NYSE | 0.8512 | 0.8166 | -0.03460 | 0.0276 | 0.0827 |

Table 7.30: Information Share Tests: PT/GG Measure: Series Bid

(a) Regulation FD: 1999-2000 PT/GG Bid

The table shows the results of t-tests of differences in information shares, for the bid series from Cincinnati and NYSE. The estimates are derived with the PT/GG measure, before and after Reg. FD and decimalization were implemented. Pre refers to the aggregate information before the regulation was implemented and Post is the aggregate information share after the regulation was in force. Panel A shows the results of the difference in mean information shares before and and after Reg. FD was implemented. Panel B shows the results of the same test for the difference between 2000 and 2001, i.e., before and after decimalization was in force.

| Exchange | Mean | | Difference | P-Value | Variance |
|---|---|---|---|---|---|
| | Pre | Post | Post-Pre | | P-Value |
| Cincinnati | 0.0315 | 0.0186 | -0.01280 | 0.6420 | <.0001 |
| NYSE | 0.9685 | 0.9814 | 0.01280 | 0.6420 | <.0001 |

(b) Decimalization: 2000-2001 PT/GG Bid

| Exchange | Mean | | Difference | P-Value | Variance |
|---|---|---|---|---|---|
| | Pre | Post | Post-Pre | | P-Value |
| Cincinnati | 0.0186 | 0.0676 | 0.04900 | 0.0309 | <.0001 |
| NYSE | 0.9814 | 0.9324 | -0.04900 | 0.0309 | <.0001 |

Table 7.31: Information Share Tests: PT/GG Measure: Series Offer

(a) Regulation FD: 1999-2000 PT/GG Offer

The table shows the results of t-tests of differences in information shares, for the offer series from Cincinnati and NYSE. The estimates are derived with the PT/GG measure, before and after Reg. FD and decimalization were implemented. Pre refers to the aggregate information before the regulation was implemented and Post is the aggregate information share after the regulation was in force. Panel A shows the results of the difference in mean information shares before and and after Reg. FD was implemented. Panel B shows the results of the same test for the difference between 2000 and 2001, i.e., before and after decimalization was in force.

| Exchange | Mean | | Difference | P-Value | Variance |
|---|---|---|---|---|---|
| | Pre | Post | Post-Pre | | P-Value |
| Cincinnati | 0.0057 | 0.0148 | 0.00916 | 0.0620 | <.0001 |
| NYSE | 0.9943 | 0.9852 | -0.00916 | 0.0620 | <.0001 |

(b) Decimalization: 2000-2001 PT/GG Offer

| Exchange | Mean | | Difference | P-Value | Variance |
|---|---|---|---|---|---|
| | Pre | Post | Post-Pre | | P-Value |
| Cincinnati | 0.0148 | 0.0218 | 0.00692 | 0.5563 | <.0001 |
| NYSE | 0.9852 | 0.9782 | -0.00692 | 0.5563 | <.0001 |

Table 7.32: Impulse Responses Tests: Series Bid

The table shows the results of t-tests of differences in convergence times, for the bid series from 1999 and 2000. That is, the period before and after Reg. FD was implemented. Pre refers to the aggregate convergence time before the regulation was implemented and Post is the aggregate after the regulation was in force.

| Reg. FD: 1999-2000 IS Bid | | | | | |
|---|---|---|---|---|---|
| Exchange | Mean | | Difference | P-Value | Variance |
| | Pre | Post | Post - Pre | | P-Value |
| Boston | 1522.00 | 1603.00 | 81.00 | 0.4413 | 0.4558 |
| Cincinnati | 1540.10 | 1652.60 | 112.50 | 0.3032 | 0.3785 |
| NYSE | 1438.00 | 1635.60 | 197.60 | 0.1026 | 0.2289 |

Table 7.33: Impulse Responses Tests: Series Offer

The table shows the results of t-tests of differences in convergence times, for the bid series from 1999 and 2000. That is, the period before and after Reg. FD was implemented. Pre refers to the aggregate convergence time before the regulation was implemented and Post is the aggregate after the regulation was in force.

| Reg. FD: 1999-2000 IS Offer | | | | | |
|---|---|---|---|---|---|
| Exchange | Mean | | Difference | P-Value | Variance |
| | Pre | Post | Post - Pre | | P-Value |
| Boston | 1606.70 | 1612.20 | 5.56 | 0.9542 | 0.4115 |
| Cincinnati | 1540.10 | 1557.80 | 17.72 | 0.8600 | 0.0540 |
| NYSE | 1552.80 | 1597.40 | 44.56 | 0.6797 | 0.0290 |

Table 7.34: Impulse Responses Tests: Series Bid

The table shows the results of t-tests of differences in convergence times, for the bid series from 2000 and 2001. That is, the period before and after decimalization was implemented. Pre refers to the aggregate convergence time before the regulation was implemented and Post is the aggregate after the regulation was in force.

Decimalization: 2000-2001 IS Bid

| Exchange | Mean | | Difference | P-Value | Variance |
|---|---|---|---|---|---|
| | Pre | Post | Post - Pre | | P-Value |
| Boston | 1603.00 | 3061.30 | 1458.20 | <.0001 | 0.0003 |
| Cincinnati | 1652.60 | 2852.50 | 1199.80 | <.0001 | 0.0003 |
| NYSE | 1635.60 | 2965.70 | 1330.10 | <.0001 | 0.0006 |

Table 7.35: Impulse Responses Tests: Series Offer

The table shows the results of t-tests of differences in convergence times, for the offer series from 2000 and 2001. That is, the period before and after decimalization was implemented. Pre refers to the aggregate convergence time before the regulation was implemented and Post is the aggregate after the regulation was in force.

Decimalization: 2000-2001 IS Offer

| Exchange | Mean | | Difference | P-Value | Variance |
|---|---|---|---|---|---|
| | Pre | Post | Post - Pre | | P-Value |
| Boston | 1612.20 | 2808.60 | 1196.40 | <.0001 | <.0001 |
| Cincinnati | 1557.80 | 2676.20 | 1118.40 | <.0001 | <.0001 |
| NYSE | 1597.40 | 2612.80 | 1015.50 | <.0001 | <.0001 |

Table 7.36: Impulse Responses Tests

The table shows the results of t-tests of differences in convergence times between the bid and offer series from 1999. That is, the period before both Reg. FD and decimalization were implemented. Pre refers to the aggregate convergence time before the regulation was implemented and Post is the aggregate after the regulation was in force.

| 1999 Bid vs. Offer | | | | | |
|---|---|---|---|---|---|
| Exchange | Mean | | Difference | P-Value | Variance |
| | Pre | Post | Post - Pre | | P-Value |
| Boston | 1522.00 | 1606.70 | 84.64 | 0.4375 | 0.7201 |
| Cincinnati | 1540.10 | 1595.10 | 54.96 | 0.6347 | 0.8311 |
| NYSE | 1438.00 | 1552.80 | 114.80 | 0.3826 | 0.8688 |

Table 7.37: Impulse Responses Tests

The table shows the results of t-tests of differences in convergence times between the bid and offer series from 2000. That is, the period when Reg. FD was implemented, but not decimalization. Pre refers to the aggregate convergence time before the regulation was implemented and Post is the aggregate after the regulation was in force.

| 2000 Bid vs. Offer | | | | | |
|---|---|---|---|---|---|
| Exchange | Mean | | Difference | P-Value | Variance |
| | Pre | Post | Post - Pre | | P-Value |
| Boston | 1603.00 | 1612.20 | -9.20 | 0.9208 | 0.6641 |
| Cincinnati | 1652.60 | 1557.80 | 94.80 | 0.2907 | 0.2869 |
| NYSE | 1635.60 | 1597.40 | 38.24 | 0.6821 | 0.2420 |

Table 7.38: Impulse Responses Tests

The table shows the results of t-tests of differences in convergence times between the bid and offer series from 2001. That is, the period when decimalization was implemented. Pre refers to the aggregate convergence time before the regulation was implemented, and Post is the aggregate after the regulation was in force.

| 2001 Bid vs. Offer | | | | | |
|---|---|---|---|---|---|
| Exchange | Mean | | Difference | P-Value | Variance |
| | Pre | Post | Post - Pre | | P-Value |
| Boston | 3061.30 | 2808.60 | 252.60 | 0.2391 | 0.8669 |
| Cincinnati | 2852.50 | 2676.20 | 176.30 | 0.4031 | 0.8678 |
| NYSE | 2965.70 | 2612.80 | 352.80 | 0.1246 | 0.7078 |

# APPENDIX A

## Tables

Table A.1: Unit Root Tests. Data Series - Quotes on NYSE, Cincinnati, Boston from Oct 30 - Dec 24 1999.

The table shows the results of the ADF test for the presence of a unit root. The series are from Boston, Cincinnati and NYSE for 1999 when neither regulation was in force.

| | Null Hypothesis: Series contains a unit root | | | | | |
|---|---|---|---|---|---|---|
| Stock | Boston | | Cincinnati | | NYSE | |
| | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value |
| Alcoa | 0.6430 | 0.8551 | 0.6876 | 0.8641 | -0.8560 | 0.8023 |
| AIG | 0.2337 | 0.7541 | 0.2440 | 0.7570 | 0.2420 | 0.7565 |
| Am Express | 0.1581 | 0.7320 | 0.1553 | 0.7312 | 0.1566 | 0.7316 |
| Boeing | -2.2396 | 0.1924 | -2.1124 | 0.2399 | -2.1579 | 0.2222 |
| BOA | -1.4460 | 0.5609 | -1.3881 | 0.5896 | -1.3960 | 0.5857 |
| Citigroup | 0.1598 | 0.7325 | 0.1986 | 0.7440 | 0.4794 | 0.8185 |
| Caterpillar | -1.5029 | 0.5322 | -1.4718 | 0.5480 | -1.5059 | 0.5306 |
| Chevron | -0.5131 | 0.4945 | -0.5157 | 0.4935 | -0.5245 | 0.4898 |
| Du Pont | -0.0876 | 0.6535 | -0.0933 | 0.6516 | -0.1062 | 0.6471 |
| Disney | 0.1209 | 0.7206 | 0.1463 | 0.7283 | 0.1301 | 0.7234 |
| General Electric | 0.2057 | 0.7461 | 0.2925 | 0.7705 | 0.2862 | 0.7688 |
| General Motors | 0.1575 | 0.7318 | 0.1686 | 0.7351 | 0.1686 | 0.7351 |
| Home Depot | 0.2156 | 0.7489 | 0.2273 | 0.7522 | 0.2281 | 0.7525 |
| IBM | 0.1349 | 0.7251 | 0.1494 | 0.7294 | 0.1485 | 0.7292 |
| J&J | -1.8876 | 0.3385 | -2.1584 | 0.2219 | -1.8958 | 0.3346 |
| JP Morgan | 0.0635 | 0.7030 | 0.0731 | 0.7060 | 0.0757 | 0.7068 |
| Coca-Cola | 0.0839 | 0.7089 | 0.0829 | 0.7086 | 0.0834 | 0.7087 |
| McDonald | -2.4131 | 0.1382 | -2.3875 | 0.1454 | -2.4032 | 0.1410 |
| 3M | -2.0537 | 0.2639 | -2.0408 | 0.2694 | -2.0823 | 0.2520 |
| Merck | -0.6480 | 0.4368 | -0.6600 | 0.4315 | -0.6536 | 0.4343 |
| Pfizer | -2.4752 | 0.1217 | -2.4579 | 0.1262 | -2.3243 | 0.1644 |
| P&G | -2.2978 | 0.1728 | -2.2781 | 0.1793 | -2.2852 | 0.1770 |
| AT&T | 0.2588 | 0.7611 | 0.2586 | 0.7610 | 0.2486 | 0.7582 |
| UTX | 0.1070 | 0.7165 | 0.1527 | 0.7304 | 0.1325 | 0.7243 |
| Wal-Mart | 0.2646 | 0.7628 | 0.2920 | 0.7703 | 0.2837 | 0.7681 |

Table A.2: Unit Root Tests. Data Series - Quotes on NYSE, Cincinnati, Boston from Oct 30 - Dec 24 2000.

The table shows the results of the ADF test for the presence of a unit root. The series are from Boston, Cincinnati and NYSE for 2000 when Reg. FD was in force.

| | Null Hypothesis: Series contains a unit root | | | | | |
|---|---|---|---|---|---|---|
| Stock | Boston | | Cincinnati | | NYSE | |
| | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value |
| | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value |
| Alcoa | 0.3959 | 0.7977 | 0.4340 | 0.8073 | 0.4244 | 0.8050 |
| AIG | -0.2209 | 0.6069 | -0.2293 | 0.6038 | -0.2209 | 0.6068 |
| Am Express | -0.4368 | 0.5255 | -0.4148 | 0.5341 | -0.4290 | 0.5286 |
| Boeing | -0.1085 | 0.6463 | -0.0608 | 0.6625 | -0.0867 | 0.6538 |
| BOA | -0.1400 | 0.6351 | -0.1226 | 0.6411 | -0.1360 | 0.6365 |
| Citigroup | -0.2785 | 0.5859 | -0.3239 | 0.5690 | -0.3140 | 0.5727 |
| Caterpillar | 0.8260 | 0.8896 | 0.8456 | 0.8930 | 0.8417 | 0.8923 |
| Chevron | -0.2479 | 0.5970 | -0.2640 | 0.5912 | -0.2519 | 0.5956 |
| Du Pont | 0.2142 | 0.7484 | 0.2264 | 0.7519 | 0.2177 | 0.7494 |
| Disney | -0.7478 | 0.3925 | -0.7674 | 0.3838 | -0.7525 | 0.3904 |
| General Electric | -0.4325 | 0.5271 | -0.4155 | 0.5338 | -0.4060 | 0.5375 |
| General Motors | -0.5642 | 0.4730 | -0.5556 | 0.4766 | -0.5513 | 0.4784 |
| Home Depot | -0.1021 | 0.6484 | -0.0979 | 0.6498 | -0.0965 | 0.6503 |
| IBM | -0.1852 | 0.6196 | -0.1634 | 0.6273 | -0.1764 | 0.6227 |
| J&J | 0.3062 | 0.7742 | 0.3171 | 0.7772 | 0.2928 | 0.7706 |
| JP Morgan | 0.0459 | 0.6975 | 0.0563 | 0.7008 | 0.0477 | 0.6980 |
| Coca-Cola | -0.0339 | 0.6707 | -0.0319 | 0.6714 | -0.0561 | 0.6633 |
| McDonald | 0.2667 | 0.7631 | 0.2471 | 0.7576 | 0.2616 | 0.7617 |
| 3M | 0.3366 | 0.7824 | 0.3608 | 0.7888 | 0.3423 | 0.7840 |
| Merck | 0.0552 | 0.7004 | 0.0815 | 0.7086 | 0.0628 | 0.7028 |
| Pfizer | -0.0008 | 0.6823 | 0.0115 | 0.6863 | -0.0193 | 0.6762 |
| P&G | -0.1548 | 0.6303 | -0.1685 | 0.6255 | -0.1574 | 0.6294 |
| AT&T | -1.0213 | 0.2763 | -1.0277 | 0.2738 | -1.0245 | 0.2751 |
| UTX | 0.3314 | 0.7810 | 0.3622 | 0.7892 | 0.3450 | 0.7847 |
| Wal-Mart | -0.0339 | 0.6714 | -0.0332 | 0.6717 | -0.0361 | 0.6707 |

Table A.3: Unit Root Tests. Data Series - Quotes on NYSE, Cincinnati, Boston from March 30 - May 30 2001.

The table shows the results of the ADF test for the presence of a unit root. The series are from Boston, Cincinnati and NYSE for 2001 when decimalization was implemented.

| | Null Hypothesis: Series contains a unit root | | | | | |
|---|---|---|---|---|---|---|
| Stock | Boston | | Cincinnati | | NYSE | |
| | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value |
| | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value |
| Alcoa | -0.0427 | 0.6684 | -0.0502 | 0.6659 | -0.0514 | 0.6655 |
| AIG | -0.5497 | 0.4791 | -0.5462 | 0.4806 | -0.5474 | 0.4801 |
| Am Express | -0.5229 | 0.4904 | -0.6750 | 0.4249 | -0.5301 | 0.4874 |
| Boeing | -0.4108 | 0.5357 | -0.4061 | 0.5375 | -0.4025 | 0.5390 |
| BOA | 0.2217 | 0.7506 | 0.2190 | 0.7498 | 0.2166 | 0.7491 |
| Citigroup | -0.8325 | 0.3555 | -0.9671 | 0.2985 | -0.9403 | 0.3095 |
| Caterpillar | -0.2855 | 0.5833 | -0.2986 | 0.5784 | -0.2937 | 0.5802 |
| Chevron | -0.2337 | 0.6023 | -0.2397 | 0.6001 | -0.2156 | 0.6088 |
| Du Pont | -0.8738 | 0.3376 | -0.9285 | 0.3144 | -0.9383 | 0.3103 |
| Disney | -0.8082 | 0.3660 | -0.8123 | 0.3642 | -0.7347 | 0.3984 |
| General Electric | -1.9042 | 0.0543 | -2.0869 | 0.0355 | -1.9944 | 0.0442 |
| General Motors | -0.4284 | 0.5288 | -0.4701 | 0.5121 | -0.4694 | 0.5124 |
| Home Depot | -0.0249 | 0.6744 | -0.0668 | 0.6604 | -0.0443 | 0.6680 |
| IBM | -0.7091 | 0.4098 | -0.7222 | 0.4040 | -0.6996 | 0.4140 |
| J&J | 0.0678 | 0.7043 | 0.1015 | 0.7148 | 0.0830 | 0.7090 |
| JP Morgan | -1.1192 | 0.2395 | -1.0853 | 0.2520 | -1.0430 | 0.2682 |
| Coca-Cola | 0.4311 | 0.8064 | 0.5059 | 0.8245 | 0.4388 | 0.8083 |
| McDonald | 0.1542 | 0.7306 | 0.2064 | 0.7460 | 0.1540 | 0.7306 |
| 3M | -0.3696 | 0.5517 | -0.3737 | 0.5501 | -0.3700 | 0.5515 |
| Merck | -0.0602 | 0.6627 | -0.0581 | 0.6634 | -0.0701 | 0.6594 |
| Pfizer | -0.4197 | 0.5321 | -0.4738 | 0.5105 | -0.4543 | 0.5184 |
| P&G | 2.0689 | 0.9913 | 2.3877 | 0.9963 | 2.3008 | 0.9953 |
| AT&T | -0.3757 | 0.5489 | -0.3847 | 0.5454 | -0.3794 | 0.5474 |
| UTX | -0.2385 | 0.6005 | -0.2129 | 0.6097 | -0.2214 | 0.6066 |
| Wal-Mart | -0.1013 | 0.6487 | -0.0793 | 0.6562 | -0.0842 | 0.6546 |

Table A.4: Granger Causality Tests - Series Bid 1999.

The table shows the results of the Granger Causality test. The test is conducted between pairs of series. BBID, CBID and NBID refer to the 1999 bid series from Boston, Cincinnati and NYSE respectively. Column two states the null hypothesis of the test, and the next two columns show the test static and the p-value

| Stock | Null Hypothesis | F-Stat | P-Value |
|---|---|---|---|
| Alcoa | CBID does not Granger-Cause BBID | 9.0849 | 0.0001 |
| AIG | NBID does not Granger-Cause BBID | 75.0947 | 0.0000 |
| Am Express | BBID does not Granger-Cause NBID | 6.1813 | 0.0021 |
| Boeing | NBID does not Granger-Cause BBID | 84.2424 | 0.0000 |
| BOA | CBID does not Granger-Cause BBID | 34.8066 | 0.0000 |
| Citigroup | BBID does not Granger-Cause CBID | 4.4161 | 0.0005 |
| Caterpillar | NBID does not Granger-Cause CBID | 23.2863 | 0.0000 |
| Chevron | BBID does not Granger-Cause NBID | 2.6614 | 0.0699 |
| Du Pont | CBID does not Granger-Cause BBID | 119.6440 | 0.0000 |
| Disney | CBID does not Granger-Cause BBID | 16.8301 | 0.0000 |
| GE | NBID does not Granger-Cause BBID | 2725.8600 | 0.0000 |
| GM | BBID does not Granger-Cause CBID | 4.9142 | 0.0074 |
| Home Depot | CBID does not Granger-Cause BBID | 22.1290 | 0.0000 |
| IBM | NBID does not Granger-Cause BBID | 211.7290 | 0.0000 |
| J&J | BBID does not Granger-Cause CBID | 5.8964 | 0.0028 |
| JP Morgan | CBID does not Granger-Cause BBID | 71.9411 | 0.0000 |
| Coca-Cola | NBID does not Granger-Cause BBID | 3.6452 | 0.0269 |
| McDonald | BBID does not Granger-Cause CBID | 2.5560 | 0.0779 |
| 3M | NBID does not Granger-Cause CBID | 128.3400 | 0.0000 |
| Merck | BBID does not Granger-Cause CBID | 7.7728 | 0.0004 |
| Pfizer | CBID does not Granger-Cause BBID | 15.8679 | 0.0000 |
| P&G | BBID does not Granger-Cause CBID | 60.6626 | 0.0000 |
| AT&T | NBID does not Granger-Cause BBID | 26.4096 | 0.0000 |
| UTX | CBID does not Granger-Cause BBID | 36.7996 | 0.0000 |
| Wal-Mart | NBID does not Granger-Cause CBID | 14.6349 | 0.0000 |

Table A.5: Granger Causality Tests - Series Offer 2000.

The table shows the results of the Granger Causality test. The test is conducted between pairs of series. BBID, CBID and NBID refer to the 2000 offer series from Boston, Cincinnati and NYSE respectively. Column two states the null hypothesis of the test, and the next two columns show the test static and the p-value

| Stock | Null Hypothesis | F-Stat | P-Value |
|---|---|---|---|
| Alcoa | COFR does not Granger-Cause BOFR | 12.6050 | 0.0000 |
| AIG | NOFR does not Granger-Cause COFR | 114.6160 | 0.0000 |
| Am Express | BOFR does not Granger-Cause COFR | 19.4151 | 0.0000 |
| Boeing | NOFR does not Granger-Cause COFR | 93.5992 | 0.0000 |
| BOA | COFR does not Granger-Cause BOFR | 5.7504 | 0.0034 |
| Citigroup | BOFR does not Granger-Cause COFR | 114.6340 | 0.0000 |
| Caterpillar | NOFR does not Granger-Cause COFR | 5.7925 | 0.0032 |
| Chevron | BOFR does not Granger-Cause NOFR | 3.0572 | 0.0472 |
| Du Pont | COFR does not Granger-Cause BOFR | 29.3071 | 0.0000 |
| Disney | NOFR does not Granger-Cause BOFR | 10.1171 | 0.0001 |
| GE | BOFR does not Granger-Cause COFR | 18.0139 | 0.0000 |
| GM | COFR does not Granger-Cause BOFR | 6.9630 | 0.0010 |
| Home Depot | NOFR does not Granger-Cause BOFR | 39.4260 | 0.0000 |
| IBM | BOFR does not Granger-Cause COFR | 279.6360 | 0.0000 |
| J&J | COFR does not Granger-Cause BOFR | 34.8058 | 0.0000 |
| JP Morgan | BOFR does not Granger-Cause COFR | 135.9700 | 0.0000 |
| Coca-Cola | NOFR does not Granger-Cause COFR | 3.0114 | 0.0508 |
| McDonald | BOFR does not Granger-Cause COFR | 17.8107 | 0.0000 |
| 3M | COFR does not Granger-Cause BOFR | 11.1634 | 0.0000 |
| Merck | BOFR does not Granger-Cause NOFR | 3.0567 | 0.0472 |
| Pfizer | NOFR does not Granger-Cause BOFR | 125.7630 | 0.0000 |
| P&G | BOFR does not Granger-Cause COFR | 28.2957 | 0.0000 |
| AT&T | COFR does not Granger-Cause BOFR | 5.6463 | 0.0038 |
| UTX | NOFR does not Granger-Cause BOFR | 9.1539 | 0.0001 |
| Wal-Mart | COFR does not Granger-Cause BOFR | 25.3244 | 0.0000 |

Table A.6: Granger Causality Tests - Series Bid 2001.

The table shows the results of the Granger Causality test. The test is conducted between pairs of series. BBID, CBID and NBID refer to the 2001 bid series from Boston, Cincinnati and NYSE respectively. Column two states the null hypothesis of the test, and the next two columns show the test static and the p-value

| Stock | Null Hypothesis | F-Stat | P-Value |
|---|---|---|---|
| Alcoa | NBID does not Granger-Cause CBID | 37.6514 | 1.00E-16 |
| AIG | CBID does not Granger-Cause BBID | 5.97793 | 0.0026 |
| Am Express | BBID does not Granger-Cause CBID | 143.694 | 6.00E-61 |
| Boeing | CBID does not Granger-Cause BBID | 79.5763 | 1.00E-34 |
| BOA | NBID does not Granger-Cause BBID | 83.7697 | 8.00E-36 |
| Citigroup | BBID does not Granger-Cause CBID | 80.4339 | 6.00E-35 |
| Caterpillar | NBID does not Granger-Cause BBID | 44.7827 | 8.00E-20 |
| Chevron | CBID does not Granger-Cause BBID | 28.9289 | 3.00E-13 |
| Du Pont | BBID does not Granger-Cause CBID | 18.227 | 1.00E-08 |
| Disney | NBID does not Granger-Cause BBID | 102.484 | 1.00E-42 |
| GE | CBID does not Granger-Cause BBID | 243.142 | 1.00E-100 |
| GM | BBID does not Granger-Cause CBID | 15.0193 | 3.00E-07 |
| Home Depot | NBID does not Granger-Cause BBID | 188.347 | 1.00E-75 |
| IBM | BBID does not Granger-Cause CBID | 29.9239 | 1.00E-13 |
| J&J | CBID does not Granger-Cause BBID | 47.5919 | 6.00E-21 |
| JP Morgan | NBID does not Granger-Cause BBID | 82.3935 | 5.00E-35 |
| Coca-Cola | CBID does not Granger-Cause BBID | 68.6566 | 8.00E-27 |
| McDonald | BBID does not Granger-Cause NBID | 2.84799 | 0.0585 |
| 3M | CBID does not Granger-Cause BBID | 2.14496 | 1.17E-01 |
| Merck | NBID does not Granger-Cause CBID | 82.3363 | 1.00E-35 |
| Pfizer | BBID does not Granger-Cause NBID | 4.46092 | 0.0117 |
| P&G | CBID does not Granger-Cause BBID | 34.1253 | 2.00E-15 |
| AT&T | NBID does not Granger-Cause CBID | 3.92241 | 0.0204 |
| UTX | NBID does not Granger-Cause CBID | 7.18535 | 8.00E-04 |
| Wal-Mart | BBID does not Granger-Cause CBID | 3.20812 | 0.0406 |

Table A.7: Cointegration Tests. Data Series - Quotes on NYSE, Cincinnati, Boston from Oct 30 - Dec 24th 1999.

The table shows the results of cointegration tests following the Johansen methodology for 1999 series. The procedure consists of the Trace and Maximum Eigenvalue tests, which test progressively, for an increasing number of cointegrating vectors, and stop when a higher number is rejected. The left side panel shows the results of the Trace test and the right shows the results of the Max Eigenvalue test

| | Trace Test | | | | | | Max Eigen Value Test | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | No. of Cointegrating Vectors | | | | | | No. of Cointegrating Vectors | | | | | |
| | None | | At Most One | | At Most Two | | None | | At Most One | | At Most Two | |
| Stock | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value |
| Alcoa | 309.3693 | 0.0001 | 103.7451 | 0.0001 | 1.425542 | 0.2325 | 205.6242 | 0.0001 | 102.3196 | 0.0001 | 1.425542 | 0.2325 |
| AIG | 4862.98 | 0.0001 | 1973.616 | 0.0001 | 0.058813 | 0.8424 | 2889.364 | 0.0001 | 1973.557 | 0.0001 | 0.058813 | 0.8424 |
| Am Express | 6601.459 | 0.0001 | 3003.793 | 0.0001 | 0.030008 | 0.8873 | 3597.666 | 0.0001 | 3003.763 | 0.0001 | 0.030008 | 0.8873 |
| Boeing | 725.6598 | 0.0001 | 345.9693 | 0.0001 | 0.287315 | 0.653 | 379.6905 | 0.0001 | 345.682 | 0.0001 | 0.287315 | 0.653 |
| BOA | 900.9564 | 0.0001 | 391.6276 | 0.0001 | 0.27705 | 0.6592 | 509.3287 | 0.0001 | 391.3506 | 0.0001 | 0.27705 | 0.6592 |
| Citigroup | 992.1327 | 0.0001 | 442.7226 | 0.0001 | 0.039954 | 0.87 | 549.4101 | 0.0001 | 442.6826 | 0.0001 | 0.039954 | 0.87 |
| Caterpillar | 799.4426 | 0.0001 | 317.0038 | 0.0001 | 0.527303 | 0.5304 | 482.4388 | 0.0001 | 316.4765 | 0.0001 | 0.527303 | 0.5304 |
| Chevron | 2854.972 | 0.0001 | 1382.827 | 0.0001 | 0.263238 | 0.6679 | 1472.145 | 0.0001 | 1382.564 | 0.0001 | 0.263238 | 0.6679 |
| Du Pont | 1989.061 | 0.0001 | 936.1916 | 0.0001 | 0.005928 | 0.9497 | 1052.869 | 0.0001 | 936.1856 | 0.0001 | 0.005928 | 0.9497 |
| Disney | 447.4963 | 0.0001 | 200.9035 | 0.0001 | 0.016117 | 0.9173 | 246.5928 | 0.0001 | 200.8874 | 0.0001 | 0.016117 | 0.9173 |
| GE | 10350.03 | 0.0001 | 4323.792 | 0.0001 | 0.0792 | 0.8173 | 6026.239 | 0.0001 | 4323.713 | 0.0001 | 0.0792 | 0.8173 |
| GM | 2186.454 | 0.0001 | 997.7189 | 0.0001 | 0.028269 | 0.8907 | 1188.736 | 0.0001 | 997.6906 | 0.0001 | 0.028269 | 0.8907 |
| Home Depot | 1990.313 | 0.0001 | 910.8347 | 0.0001 | 0.045637 | 0.8611 | 1079.478 | 0.0001 | 910.7891 | 0.0001 | 0.045637 | 0.8611 |
| IBM | 4408.05 | 0.0001 | 2043.65 | 0.0001 | 0.02094 | 0.9058 | 2364.4 | 0.0001 | 2043.629 | 0.0001 | 0.02094 | 0.9058 |
| J&J | 2015.172 | 0.0001 | 926.7169 | 0.0001 | 0.239835 | 0.6829 | 1088.455 | 0.0001 | 926.4771 | 0.0001 | 0.239835 | 0.6829 |
| JP Morgan | 4949.725 | 0.0001 | 2160.818 | 0.0001 | 0.004891 | 0.9542 | 2788.907 | 0.0001 | 2160.813 | 0.0001 | 0.004891 | 0.9542 |
| Coca-Cola | 195.8643 | 0.0001 | 86.55017 | 0.0001 | 0.00892 | 0.9386 | 109.3141 | 0.0001 | 86.54125 | 0.0001 | 0.00892 | 0.9386 |
| McDonald | 739.3809 | 0.0001 | 317.2939 | 0.0001 | 0.000861 | 0.9828 | 422.087 | 0.0001 | 317.293 | 0.0001 | 0.000861 | 0.9828 |
| 3M | 3078.643 | 0.0001 | 1204.497 | 0.0001 | 0.010156 | 0.9344 | 1874.145 | 0.0001 | 1204.487 | 0.0001 | 0.010156 | 0.9344 |
| Merck | 1548.844 | 0.0001 | 668.6904 | 0.0001 | 0.43759 | 0.5717 | 880.1539 | 0.0001 | 668.2528 | 0.0001 | 0.43759 | 0.5717 |
| Pfizer | 348.3204 | 0.0001 | 131.5496 | 0.0001 | 0.280847 | 0.6569 | 216.7708 | 0.0001 | 131.2688 | 0.0001 | 0.280847 | 0.6569 |
| P&G | 4758.482 | 0.0001 | 2070.707 | 0.0001 | 0.088406 | 0.807 | 2687.774 | 0.0001 | 2070.619 | 0.0001 | 0.088406 | 0.807 |
| AT&T | 870.3835 | 0.0001 | 355.1213 | 0.0001 | 0.061421 | 0.839 | 515.2622 | 0.0001 | 355.0598 | 0.0001 | 0.061421 | 0.839 |
| UTX | 1239.129 | 0.0001 | 498.037 | 0.0001 | 0.016605 | 0.9161 | 741.0921 | 0.0001 | 498.0204 | 0.0001 | 0.016605 | 0.9161 |
| Wal-Mart | 1281.725 | 0.0001 | 540.3595 | 0.0001 | 0.082145 | 0.8139 | 1281.725 | 0.0001 | 540.3595 | 0.0001 | 0.082145 | 0.8139 |

Table A.8: Cointegration Tests. Data Series - Quotes on NYSE, Cincinnati, Boston from Oct 30 - Dec 24th 2000.

The table shows the results of cointegration tests following the Johansen methodology for the 2000 series. The procedure consists of the Trace and Maximum Eigenvalue tests, which test progressively, for an increasing number of cointegrating vectors, and stop when a higher number is rejected. The left side panel shows the results of the Trace test and the right shows the results of the Max Eigenvalue test

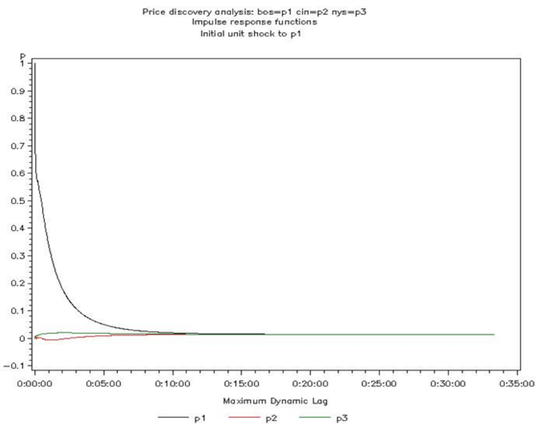
| | Trace Test | | | | | | Max Eigen Value Test | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | No. of Cointegrating Vectors | | | | | | No. of Cointegrating Vectors | | | | | |
| | None | | At Most One | | At Most Two | | None | | At Most One | | At Most Two | |
| Stock | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value |
| Alcoa | 191.6635 | 0.0001 | 61.44068 | 0.0001 | 0.200303 | 0.7101 | 130.2228 | 0.0001 | 61.24038 | 0.0001 | 0.200303 | 0.7101 |
| AIG | 2055.963 | 0.0001 | 978.641 | 0.0001 | 0.046467 | 0.8598 | 1077.322 | 0.0001 | 978.5946 | 0.0001 | 0.046467 | 0.8598 |
| Am Express | 1848.244 | 0.0001 | 823.1802 | 0.0001 | 0.199748 | 0.7105 | 1025.064 | 0.0001 | 822.9805 | 0.0001 | 0.199748 | 0.7105 |
| Boeing | 1654.766 | 0.0001 | 728.352 | 0.0001 | 0.005508 | 0.9513 | 926.4145 | 0.0001 | 728.3465 | 0.0001 | 0.005508 | 0.9513 |
| BOA | 352.4507 | 0.0001 | 155.9736 | 0.0001 | 0.022673 | 0.902 | 196.4771 | 0.0001 | 155.951 | 0.0001 | 0.022673 | 0.902 |
| Citigroup | 1570.331 | 0.0001 | 644.3432 | 0.0001 | 0.096712 | 0.7982 | 925.9876 | 0.0001 | 644.2465 | 0.0001 | 0.096712 | 0.7982 |
| Caterpillar | 486.5303 | 0.0001 | 176.3964 | 0.0001 | 0.501595 | 0.5418 | 310.134 | 0.0001 | 175.8948 | 0.0001 | 0.501595 | 0.5418 |
| Chevron | 1050.309 | 0.0001 | 496.4211 | 0.0001 | 0.065723 | 0.8335 | 553.8878 | 0.0001 | 496.3553 | 0.0001 | 0.065723 | 0.8335 |
| Du Pont | 950.9755 | 0.0001 | 417.7893 | 0.0001 | 0.044766 | 0.8624 | 533.1862 | 0.0001 | 417.7445 | 0.0001 | 0.044766 | 0.8624 |
| Disney | 439.3637 | 0.0001 | 171.7326 | 0.0001 | 0.533797 | 0.5275 | 267.6311 | 0.0001 | 171.1988 | 0.0001 | 0.533797 | 0.5275 |
| General Electric | 1095.14 | 0.0001 | 478.8661 | 0.0001 | 0.168037 | 0.7344 | 616.2735 | 0.0001 | 478.698 | 0.0001 | 0.168037 | 0.7344 |
| General Motors | 950.7383 | 0.0001 | 428.9882 | 0.0001 | 0.326423 | 0.63 | 521.7501 | 0.0001 | 428.6618 | 0.0001 | 0.326423 | 0.63 |
| Home Depot | 682.5252 | 0.0001 | 275.1011 | 0.0001 | 0.009214 | 0.9377 | 407.4241 | 0.0001 | 275.0919 | 0.0001 | 0.009214 | 0.9377 |
| IBM | 3556.731 | 0.0001 | 1709.798 | 0.0001 | 0.032784 | 0.8822 | 1846.933 | 0.0001 | 1709.766 | 0.0001 | 0.032784 | 0.8822 |
| J&J | 1519.337 | 0.0001 | 629.1873 | 0.0001 | 0.101938 | 0.7929 | 890.1495 | 0.0001 | 629.0853 | 0.0001 | 0.101938 | 0.7929 |
| JP Morgan | 8754.021 | 0.0001 | 4333.364 | 0.0001 | 0.003494 | 0.9605 | 4420.657 | 0.0001 | 4333.36 | 0.0001 | 0.003494 | 0.9605 |
| Coca-Cola | 166.2393 | 0.0001 | 68.63755 | 0.0001 | 0.000213 | 0.9922 | 97.60177 | 0.0001 | 68.63734 | 0.0001 | 0.000213 | 0.9922 |
| McDonald | 287.6465 | 0.0001 | 116.2116 | 0.0001 | 0.065777 | 0.8334 | 171.4349 | 0.0001 | 116.1458 | 0.0001 | 0.065777 | 0.8334 |
| 3M | 2199.947 | 0.0001 | 899.1549 | 0.0001 | 0.124988 | 0.7708 | 1300.792 | 0.0001 | 899.0299 | 0.0001 | 0.124988 | 0.7708 |
| Merck | 1780.195 | 0.0001 | 828.1046 | 0.0001 | 0.004527 | 0.9556 | 952.09 | 0.0001 | 828.1 | 0.0001 | 0.004527 | 0.9556 |
| Pfizer | 807.6914 | 0.0001 | 340.2465 | 0.0001 | 9.23E-05 | 0.9932 | 467.4449 | 0.0001 | 340.2464 | 0.0001 | 9.23E-05 | 0.9932 |
| P&G | 1585.015 | 0.0001 | 681.235 | 0.0001 | 0.025651 | 0.8958 | 903.7799 | 0.0001 | 681.2093 | 0.0001 | 0.025651 | 0.8958 |
| AT&T | 271.8902 | 0.0001 | 105.9001 | 0.0001 | 1.043453 | 0.3567 | 165.9901 | 0.0001 | 104.8566 | 0.0001 | 1.043453 | 0.3567 |
| UTX | 1589.059 | 0.0001 | 689.0014 | 0.0001 | 0.124845 | 0.7709 | 900.0578 | 0.0001 | 688.8765 | 0.0001 | 0.124845 | 0.7709 |
| Wal-Mart | 1208.38 | 0.0001 | 505.1175 | 0.0001 | 9.32E-06 | 0.9977 | 703.2621 | 0.0001 | 505.1175 | 0.0001 | 9.32E-06 | 0.9977 |

Table A.9: Cointegration Tests. Data Series - Quotes on NYSE, Cincinnati, Boston from March 30 - May 30th 2001.

The table shows the results of cointegration tests following the Johansen methodology for the 2001 series. The procedure consists of the Trace and Maximum Eigenvalue tests, which test progressively, for an increasing number of cointegrating vectors, and stop when a higher number is rejected. The left side panel shows the results of the Trace test and the right shows the results of the Max Eigenvalue test

| | Trace Test | | | | | | Max Eigen Value Test | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | No. of Cointegrating Vectors | | | | | | No. of Cointegrating Vectors | | | | | |
| | None | | At Most One | | At Most Two | | None | | At Most One | | At Most Two | |
| Stock | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value | Statistic | P-Value |
| Alcoa | 521.2766 | 0.0001 | 244.2352 | 0.0001 | 0.004029 | 0.9584 | 277.0414 | 0.0001 | 244.2312 | 0.0001 | 0.004029 | 0.9584 |
| AIG | 910.1839 | 0.0001 | 360.7269 | 0.0001 | 0.259468 | 0.6702 | 549.457 | 0.0001 | 360.4674 | 0.0001 | 0.259468 | 0.6702 |
| Am Express | 1046.587 | 0.0001 | 363.0064 | 0.0001 | 0.360832 | 0.611 | 683.5803 | 0.0001 | 362.6455 | 0.0001 | 0.360832 | 0.611 |
| Boeing | 1815.872 | 0.0001 | 793.3161 | 0.0001 | 0.161733 | 0.7394 | 1022.556 | 0.0001 | 793.1544 | 0.0001 | 0.161733 | 0.7394 |
| BOA | 1240.444 | 0.0001 | 449.4804 | 0.0001 | 0.047464 | 0.8584 | 790.9631 | 0.0001 | 449.433 | 0.0001 | 0.047464 | 0.8584 |
| Citigroup | 1169.177 | 0.0001 | 505.7142 | 0.0001 | 0.788872 | 0.4312 | 663.4625 | 0.0001 | 504.9253 | 0.0001 | 0.788872 | 0.4312 |
| Caterpillar | 861.6856 | 0.0001 | 396.3081 | 0.0001 | 0.084191 | 0.8117 | 465.3775 | 0.0001 | 396.2239 | 0.0001 | 0.084191 | 0.8117 |
| Chevron | 1804.319 | 0.0001 | 691.9426 | 0.0001 | 0.046529 | 0.8597 | 1112.376 | 0.0001 | 691.896 | 0.0001 | 0.046529 | 0.8597 |
| Du Pont | 566.2221 | 0.0001 | 198.9177 | 0.0001 | 0.802822 | 0.4266 | 367.3044 | 0.0001 | 198.1149 | 0.0001 | 0.802822 | 0.4266 |
| Disney | 434.6218 | 0.0001 | 200.6994 | 0.0001 | 0.634951 | 0.4862 | 233.9224 | 0.0001 | 200.0645 | 0.0001 | 0.634951 | 0.4862 |
| GE | 1477.18 | 0.0001 | 703.6719 | 0.0001 | 4.143843 | 0.0496 | 773.5083 | 0.0001 | 699.5281 | 0.0001 | 4.143843 | 0.0496 |
| GM | 1541.158 | 0.0001 | 620.2845 | 0.0001 | 0.225407 | 0.6926 | 920.8734 | 0.0001 | 620.0591 | 0.0001 | 0.225407 | 0.6926 |
| Home Depot | 902.8854 | 0.0001 | 429.972 | 0.0001 | 3.07E-06 | 0.9983 | 472.9134 | 0.0001 | 429.972 | 0.0001 | 3.07E-06 | 0.9983 |
| IBM | 2371.579 | 0.0001 | 550.5596 | 0.0001 | 0.49208 | 0.5461 | 1821.019 | 0.0001 | 550.0675 | 0.0001 | 0.49208 | 0.5461 |
| J&J | 976.0285 | 0.0001 | 403.3318 | 0.0001 | 0.006999 | 0.9454 | 572.6967 | 0.0001 | 403.3248 | 0.0001 | 0.006999 | 0.9454 |
| JP Morgan | 831.0306 | 0.0001 | 265.8578 | 0.0001 | 1.084788 | 0.3462 | 565.1728 | 0.0001 | 264.773 | 0.0001 | 1.084788 | 0.3462 |
| Coca-Cola | 363.0269 | 0.0001 | 146.3121 | 0.0001 | 0.320057 | 0.6337 | 216.7149 | 0.0001 | 145.992 | 0.0001 | 0.320057 | 0.6337 |
| McDonald | 515.7587 | 0.0001 | 194.1383 | 0.0001 | 0.038788 | 0.8719 | 321.6204 | 0.0001 | 194.0995 | 0.0001 | 0.038788 | 0.8719 |
| 3M | 5120.989 | 0.0001 | 2377.552 | 0.0001 | 0.134465 | 0.7623 | 2743.436 | 0.0001 | 2377.418 | 0.0001 | 0.134465 | 0.7623 |
| Merck | 1294.593 | 0.0001 | 515.6774 | 0.0001 | 0.001351 | 0.977 | 778.9155 | 0.0001 | 515.676 | 0.0001 | 0.001351 | 0.977 |
| Pfizer | 698.6654 | 0.0001 | 300.3457 | 0.0001 | 1.80E-01 | 0.7253 | 398.3197 | 0.0001 | 300.1658 | 0.0001 | 1.80E-01 | 0.7253 |
| P&G | 1493.984 | 0.0001 | 407.9211 | 0.0001 | 5.283879 | 0.0256 | 1086.063 | 0.0001 | 402.6373 | 0.0001 | 5.283879 | 0.0256 |
| AT&T | 239.2561 | 0.0001 | 109.1218 | 0.0001 | 0.143405 | 0.7546 | 130.1343 | 0.0001 | 108.9784 | 0.0001 | 0.143405 | 0.7546 |
| UTX | 1398.406 | 0.0001 | 523.4039 | 0.0001 | 0.054054 | 0.8489 | 875.0018 | 0.0001 | 523.3499 | 0.0001 | 0.054054 | 0.8489 |
| Wal-Mart | 1128.784 | 0.0001 | 528.7876 | 0.0001 | 8.94E-03 | 0.9386 | 599.9964 | 0.0001 | 528.7787 | 0.0001 | 8.94E-03 | 0.9386 |

## A.1 Figures

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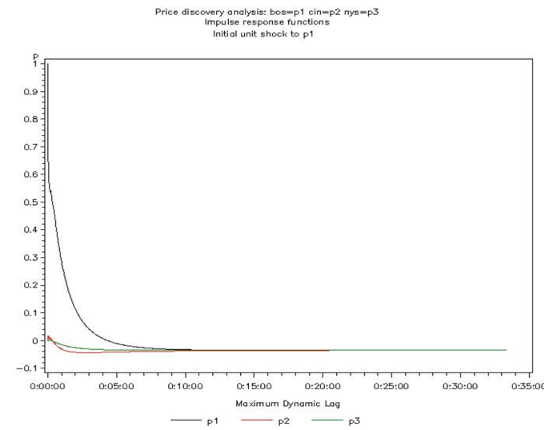


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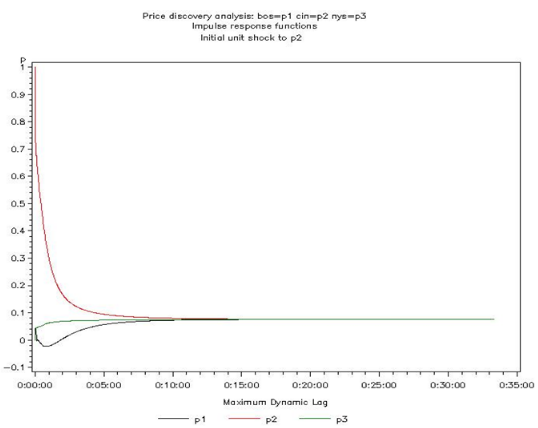


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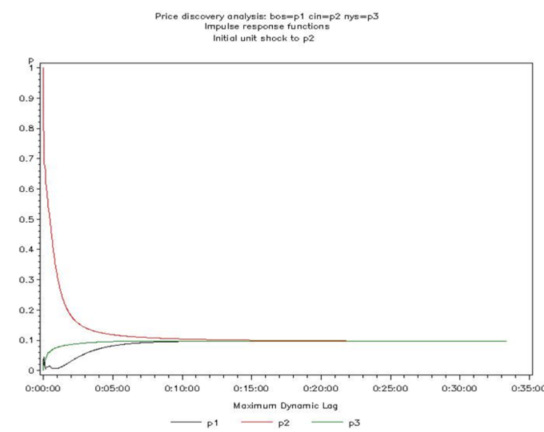
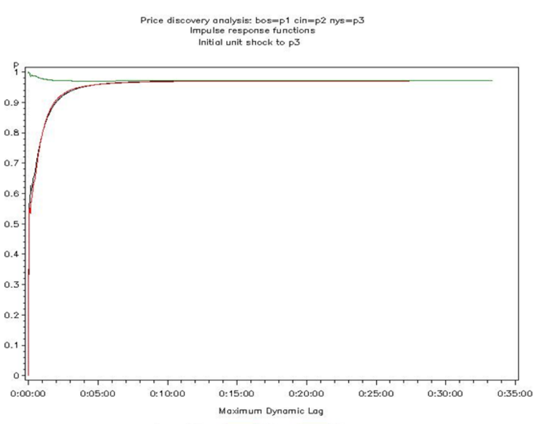
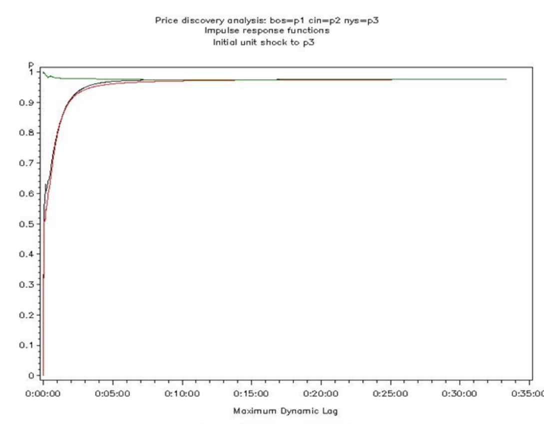



(d)

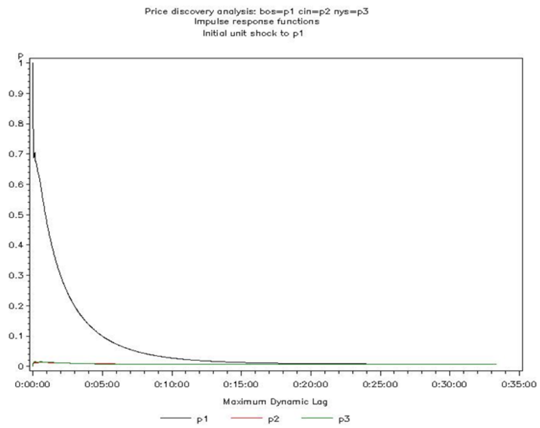



(e)

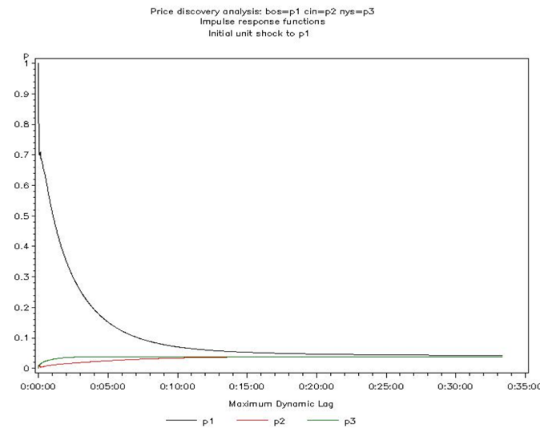



(f)

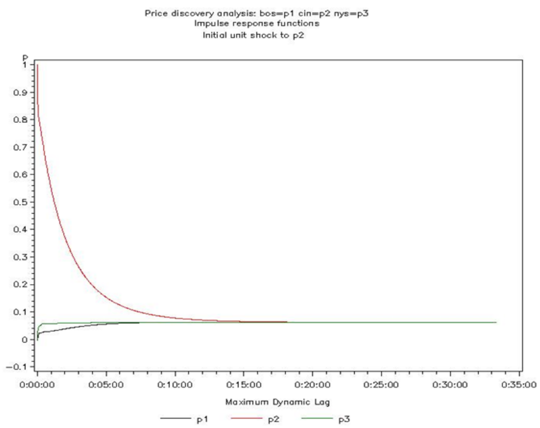
Figure A.1: Impulse Response Functions: Series 1999



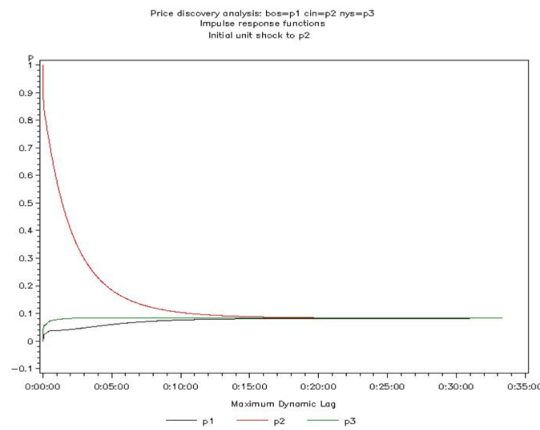

(a)



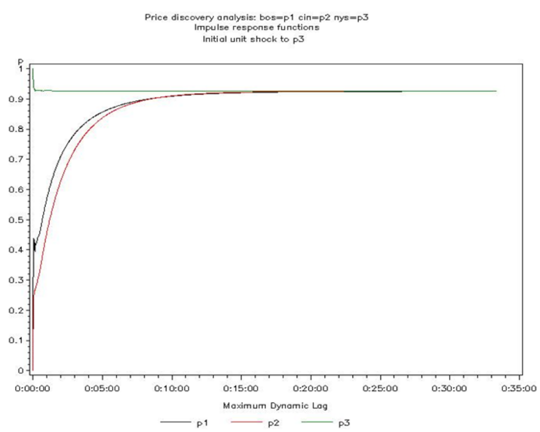

(b)



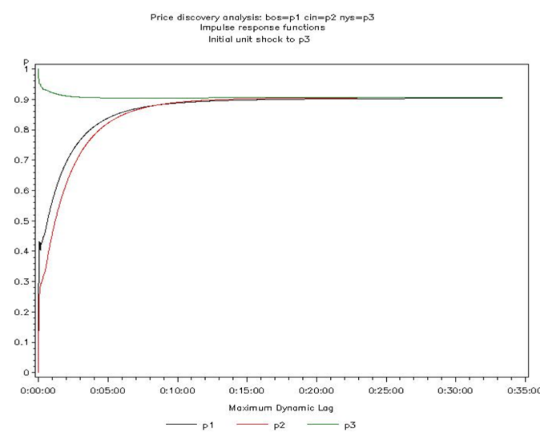

(c)




(d)

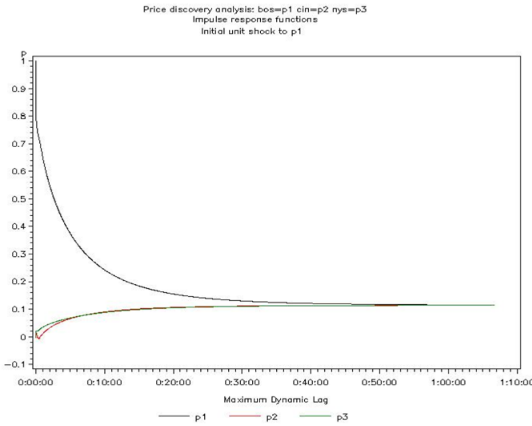



(e)

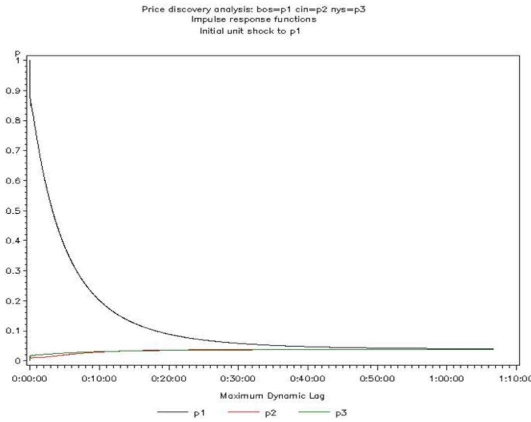



(f)

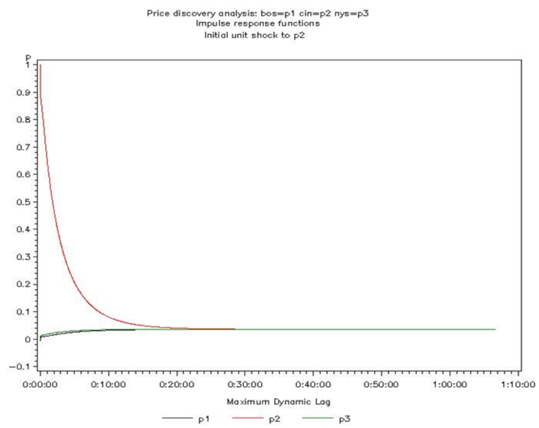
Figure A.2: Impulse Response Functions: Series 2000



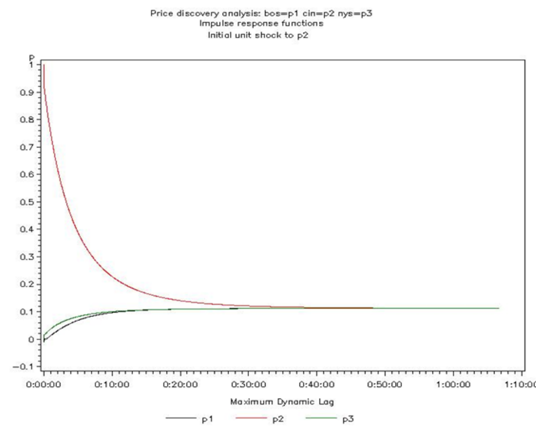

(a)



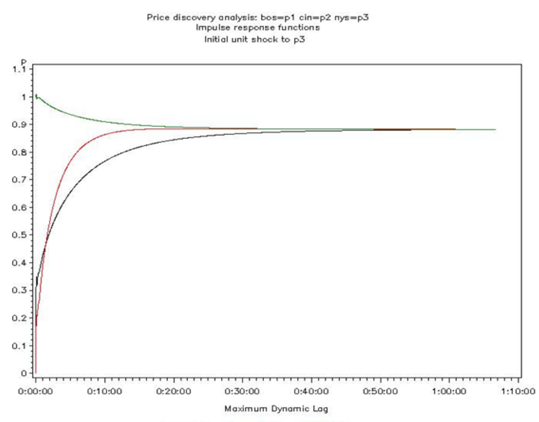

(b)



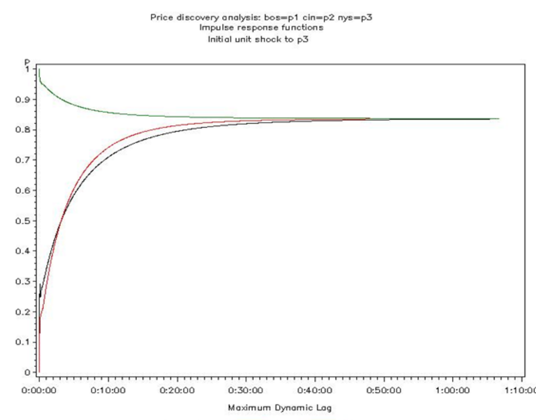

(c)




(d)




(e)




(f)

Figure A.3: Impulse Response Functions: Series 2001

# APPENDIX B

## Granger Representation Theorem

### B.1 Definitions

Let $X_t = (x_1, x_2, \ldots, x_k)^{'}$ be a $k$ component vector of $I(d)$ variables i.e., $X_t \sim I(d)$

If the components of $X_t$ are cointegrated then there exists a vector $\beta$ such that $\beta^{'} X_t \sim I(d-b)$ where $d \geq b > 0$ and $\beta$ is a cointegrating vector.

If $X_t$ is a $(k\text{x}1)$ with $k > 2$ then there can be more than one cointegrating vector and $\beta$ is a $(n\text{x}r)$ matrix whose columns are cointegrating vectors. Cointegrating rank $rk(\beta) = r \leq (k-1)$.

A time series vector $Y_t$ has an error correcting representation if it can be expressed as

$$A(L)(1-L)Y_t = -\alpha z_{t-1} + e_t \tag{B.1}$$

where $e_t$ is stationary, $L$ is the lag operator, $A(0) = I_n$. $z_t = \beta^{'} Y_t$ and $\alpha$ is a vector of adjustment coefficients.

## B.2 Granger Representation Theorem

The following proof is from Banerjee et al. (**?**): Let $X_t = (x_1, x_2, \ldots, x_n)'$ be an n-variate vector of $I(1)$ variables and if it can be written as a VAR

$$X_t = \mu + \sum_{i=1}^{k} \pi_i X_{t-i} + \varepsilon_t \tag{B.2}$$

and the terms $X_0, \ldots, X_(k-1)$ are fixed, then there is an Error Correction Representation

$$\Delta X_t = \mu + \Pi X_(t-1) + \sum_{i=1}^{k-1} \Gamma_i (1-L) L^i X_t + \varepsilon_t \tag{B.3}$$

or,

$$\Pi(L) X_t = \mu + \varepsilon_t, \quad \text{for} t = 1, 2, \ldots, T \tag{B.4}$$

Where: $\Pi(L) = (1-L)I_n - \sum_{i=1}^{k-1} \Gamma_i (1-L) L^i - \Pi L^k$ $\Gamma_i = -I_n + \pi_1 + \pi_2 + \ldots + \pi_i$ for $i = 1, 2, \ldots, k$, $\Gamma_k = \Pi = -\Pi(1)$

Equation B.3 can be written as

$$\Pi(L) X_t = -\Pi X_{t-k} + \Psi(L) \Delta X_t = \mu + \varepsilon_t \tag{B.5}$$

where $\Psi(L) = (1-L)^{-1} \left( \Pi(L) - \Pi(1) L^k \right) = I_n - \sum_{i=1}^{k-1} \Gamma_i L^i$

### B.2.1 Assumptions

**A1.** The characteristic polynomial: $\Pi(z) = (1-z)I_n - \sum_{i=1}^{k-1} \Gamma_i (1-z) z^i - \Pi z^k$ has roots outside or on the unit circle, i.e., $z \geq 1$.

**A2.** $rk(\Pi) = r < n$ therefore it can be expressed as the product of two $n$x$r$ matrices $\alpha$ and $\beta$ which both have rank $r$. Therefore $\Pi = \alpha\beta'$.

**A3.** The $(n-r)$x$(n-r)$ matrix $\alpha'_{\perp}\Psi\beta_{\perp}$ has full rank $(n-r)$.

The Error Correction Representation has the following properties:

**P1.** $\Delta X_t$ is stationary.

**P2.** $\beta' X_t$ is stationary.

**P3.** $E\left[\Delta X_t\right] = \beta_{\perp}\left(\alpha'_{\perp}\Psi\beta_{\perp}\right)^{-1}\alpha'_{\perp}\mu$

**P4.** $E\left[\beta' X_t\right] = -(\alpha'\alpha)^{-1}\alpha'\mu + (\alpha'\alpha)^{-1}\left(\alpha'_{\perp}\Psi\beta_{\perp}\right)\left(\alpha'_{\perp}\Psi\beta_{\perp}\right)^{-1}\alpha'_{\perp}\mu$

**P5.** $\Delta X_t$ has finite MA representation $\Delta X_t = C(L)(\mu + \varepsilon_t)$

**P6.** $C(1) = \beta_{\perp}\left(\alpha'_{\perp}\Psi\beta_{\perp}\right)^{-1}\alpha'_{\perp}$ with rank $(n-r)$.

**P7.** $\beta' C(1) = 0_{(r\text{x}n)}$ and $C(1)\alpha = 0_{(n\text{x}r)}$.

**P8.** $X_t = X_0 + \Psi(1)\sum\limits_{i=1}^{t}\varepsilon_t + \tau t + S_t$ where $C(L) = C(1) + (1-L)C^*(L)$, $\tau = C(1)\mu$, $S_t = C^*(L)\varepsilon_t$

### B.2.2 Proof:

To prove **P1 & P2,** i.e., $\Delta X_t$ and $\beta' X_t$, are stationary, multiply Equation B.5 by $\alpha'$ and $\alpha'_{\perp}$ using $\Pi = \alpha\beta'$ and $\alpha'_{\perp}\alpha = 0$ we get

$$\alpha'\alpha\beta' X_t + \alpha'\Psi(L)\Delta X_t = \alpha'(\mu + \varepsilon_t) \tag{B.6}$$

$$\alpha'_{\perp}\Psi(L)\Delta X_t = \alpha'_{\perp}(\mu + \varepsilon_t) \tag{B.7}$$

This system is not invertible since $\pi$ is not invertible. Define $\omega_t = (\beta'\beta)^{-1}\beta' X_t$ and $\upsilon_t = (\beta'_{\perp}\beta_{\perp})^{-1}\beta'_{\perp}\Delta X_t$, let $\overline{\beta} = \beta(\beta'\beta)^{-1}$, $\overline{\beta_{\perp}} = (\beta'_{\perp}\beta_{\perp})^{-1}\beta'_{\perp}$ if $R = (\beta, \beta_{\perp})$ then

$R(R^{'}R)^{-1}R^{'} = I_n$, therefore $\left(\beta\overline{\beta} + \beta_{\perp}\overline{\beta_{\perp}^{'}}\right) = I_n$. $\Delta X_t = \left(\beta\overline{\beta} + \beta_{\perp}\overline{\beta_{\perp}^{'}}\right)\Delta X_t = \beta\Delta\omega_t + \beta_{\perp}\upsilon_t$ substituting in B.6 and B.7, we get

$$-(\alpha^{'}\alpha)(\beta^{'}\beta)\omega_t + \alpha^{'}\Psi(L)\beta\Delta\omega_t + \alpha^{'}\Psi(L)\beta_{\perp}\upsilon_t = \alpha^{'}(\mu + \varepsilon_t) \tag{B.8}$$

$$\alpha_{\perp}^{'}\Psi(L)\beta\Delta\omega_t + \alpha_{\perp}^{'}\Psi(L)\beta_{\perp}\upsilon_t = \alpha_{\perp}^{'}(\mu + \varepsilon_t) \tag{B.9}$$

Equations for $\omega_t$ and $\upsilon_t$ can be written in AR as $\tilde{A}(L)(\omega_t^{'}\upsilon_t^{'})^{'} = (\alpha, \alpha_{\perp})^{'}(\mu + \varepsilon_t)$ and the characteristic polynomial is:

$$\tilde{A}(z) = \begin{bmatrix} -(\alpha^{'}\alpha)(\beta^{'}\beta)\omega_t + \alpha^{'}\Psi(z)\beta(1-z) & \alpha^{'}\Psi(z)\beta_{\perp} \\ \alpha_{\perp}^{'}\Psi(z)\beta(1-z) & \alpha_{\perp}^{'}\Psi(z)\beta_{\perp} \end{bmatrix} \tag{B.10}$$

$\left|\tilde{A}(z)\right| = (-1)^r \left|\alpha^{'}\alpha\right| \; \left|\beta^{'}\beta\right| \; \left|\alpha_{\perp}^{'}\Psi\beta_{\perp}\right| \neq 0$ by **A2** and **A3** or $z = 1$ is not a root, for $z \neq 1$.

$$\tilde{A}(z) = (\alpha, \alpha_{\perp})^{'}\Pi(z)\left[\beta, \beta_{\perp}(1-z)^{-1}\right] \tag{B.11}$$

and

$$\left|\tilde{A}(z)\right| = |\alpha, \alpha_{\perp}| \; |\Pi(z)| \; |\beta, \beta_{\perp}| \, (1-z)^{-(n-r)} \tag{B.12}$$

For $z \neq 1$, $\left|\tilde{A}(z)\right| = 0$ iff $|\Pi(z)| = 0$. Consequently, all the roots of $\tilde{A}(z)$ are outside the unit circle. Since $\Delta X_t = \beta\Delta\omega_t + \beta_{\perp}\upsilon_t$, stationarity of $\omega_t$ and $\upsilon_t$ ensures that $\Delta X_t$ is stationary. Since $\beta^{'}X_t = (\beta^{'}\beta)\omega_t$, $\beta^{'}X_t$ is also stationary. **P3** and **P4** are proved as follows:

$$(\omega_t^{'}\upsilon_t^{'})^{'} = \tilde{A}(L)^{-1}(\alpha, \alpha_{\perp})^{'}(\mu + \varepsilon_t) \tag{B.13}$$

Therefore $E\left[(\omega_t' \upsilon_t')'\right] = \tilde{A}(1)^{-1}(\alpha, \alpha_\perp)'\mu$

$$\tilde{A}(1) = \begin{bmatrix} -(\alpha'\alpha)(\beta'\beta) & \alpha'\Psi(1)\beta_\perp \\ 0 & \alpha_\perp'\Psi(1)\beta_\perp \end{bmatrix} \tag{B.14}$$

on inverting the matrix:

$$\tilde{A}(1)^{-1} = \begin{bmatrix} -(\beta'\beta)^{-1}(\alpha'\alpha)^{-1} & (\beta'\beta)^{-1}(\alpha'\alpha)^{-1}\alpha'\Psi(1)\beta_\perp(\alpha_\perp'\Psi(1)\beta_\perp)^{-1} \\ 0 & \alpha_\perp'\Psi(1)\beta_\perp \end{bmatrix} \tag{B.15}$$

$$E\left[\omega_t\right] = -(\beta'\beta)^{-1}(\alpha'\alpha)^{-1}\alpha'\mu + (\beta'\beta)^{-1}(\alpha'\alpha)^{-1}\alpha'\Psi(1)\beta_P\perp(\alpha_\perp'\Psi(1)\beta_\perp)^{-1}\alpha_\perp'\mu \tag{B.16}$$

$$E\left[\upsilon_t\right] = (\alpha_\perp'\Psi(1)\beta_\perp)^{-1}\alpha_\perp'\mu \tag{B.17}$$

from Equations B.16 and B.17, we obtain $E\left[\Delta X_t\right] = \beta_\perp E\left[\upsilon_t\right] + \beta E\left[\Delta\omega_t\right]$ since $E\left[\Delta\omega_t\right] = 0$.

$$E\left[\Delta X_t\right] = \beta_\perp(\alpha_\perp'\Psi(1)\beta_\perp)^{-1}\alpha_\perp'\mu \ : \ \textbf{P3 is proved} \tag{B.18}$$

$$\begin{aligned} E\left[\beta' X_t\right] &= E\left[(\beta'\beta)\omega_t\right] = (\beta'\beta)E\left[\omega_t\right] = \\ &- (\alpha'\alpha)^{-1}\alpha'\mu + (\alpha'\alpha)^{-1}\left(\alpha_\perp'\Psi\beta_\perp\right)\left(\alpha_\perp'\Psi\beta_\perp\right)^{-1}\alpha_\perp'\mu \ : \ \textbf{P4 is proved} \end{aligned} \tag{B.19}$$

We have

$(\omega_t' \upsilon_t')' = \left[\tilde{A}(L)\right]^{-1}\left[(\alpha, \alpha_\perp)'(\mu + \varepsilon_t)\right]$.

However,

$$\begin{aligned} \Delta X_t &= \alpha\Delta\omega_t + \beta_\perp\upsilon_t \\ &= \left[\beta(1-L), \beta_\perp\right](\omega_t', \upsilon_t')' \\ &= \left[\beta(1-L), \beta_\perp\right]\left[\tilde{A}(L)\right]^{-1}\left[(\alpha, \alpha_\perp)'(\mu + \varepsilon_t)\right] \\ &= C(L)(\mu + \varepsilon_t) \end{aligned} \tag{B.20}$$

where $C(L) = [\beta(1-L), \beta_\perp] \left[\tilde{A}(L)\right]^{-1} (\alpha, \alpha_\perp)'$. **This proves P5**

We have, $C(1) = [0, \beta_\perp] \left[\tilde{A}(L)\right]^{-1} (\alpha, \alpha_\perp^{'})$.

Since $\beta(1-L) = 0$ at $L = 1$, substituting for $\left[\tilde{A}(1)\right]^{-1}$,

$$C(1) = \beta_\perp (\alpha_\perp^{'} \Psi(1) \beta_\perp)^{-1} \alpha_\perp^{'} \tag{B.21}$$

we know $\beta_\perp$, $\alpha_\perp^{'}$ and $(\alpha_\perp^{'} \Psi(1)\beta_\perp)^{-1}$ have rank $(n-r)$, so $rk(C(1)) = (n-r)$.

**This proves P6 and P7**

Writing $C(L) = C(1) + (1-L)C^*(L)$ from P5,

$$\begin{aligned} \Delta X_t &= C(1)\mu + C(1)\varepsilon_t + (1-L)C^*(L)\mu + (1-L)C^*(L)\varepsilon_t \qquad \text{(B.22)} \\ &= C(1)\mu + C(1)\varepsilon_t + (1-L)C^*(L)\varepsilon_t \end{aligned}$$

By backward substitution we obtain

$$X_t = X_0 + C(1) \sum_{i=1}^{t} \varepsilon_i + C(1)\mu t + S_t \quad \textbf{P8 is proved} \tag{B.23}$$

# APPENDIX C

## Selective Disclosure and Insider Trading

### C.1 SECURITIES AND EXCHANGE COMMISSION

**17 CFR Parts 240, 243, and 249**

**Release Nos. 33-7881, 34-43154, IC-24599, File No. S7-31-99**

**RIN 3235-AH82**

**Selective Disclosure and Insider Trading**

**AGENCY:** Securities and Exchange Commission.

**ACTION:** Final rule.

**SUMMARY:** The Securities and Exchange Commission is adopting new rules to address three issues: the selective disclosure by issuers of material nonpublic information; when insider trading liability arises in connection with a trader's "use" or "knowing possession" of material nonpublic information; and when the breach of a family or other non-business relationship may give rise to liability under the misappropriation theory of insider trading. The rules are designed to promote the full and fair disclosure of information by issuers, and to clarify and enhance existing prohibitions against insider trading.

**EFFECTIVE DATE:** The new rules and amendments will take effect October 23, 2000.

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## C.2 SUPPLEMENTARY INFORMATION

The Securities and Exchange Commission today is adopting new rules: Regulation FD[1], Rule 10b5-1[2], and Rule 10b5-2[3]. Additionally, the Commission is adopting amendments to Form 8-K[4].

### C.2.1 I. Executive Summary

We are adopting new rules and amendments to address the selective disclosure of material nonpublic information by issuers and to clarify two issues under the law of insider trading. In response to the comments we received on the proposal, we have made several modifications, as discussed below, in the final rules.

Regulation FD (Fair Disclosure) is a new issuer disclosure rule that addresses selective disclosure. The regulation provides that when an issuer, or person acting on its behalf, discloses material nonpublic information to certain enumerated persons (in general, securities market professionals and holders of the issuer's securities who may well trade on the basis of the information), it must make public disclosure of that information. The timing of the required public disclosure depends on whether the selective disclosure was intentional or non-intentional; for an intentional selective disclosure, the issuer must make public disclosure simultaneously; for a non-intentional disclosure, the issuer must make

[1]http://www.sec.gov/rules/final/33-7881.htm#P12_1307
[2]http://www.sec.gov/rules/final/33-7881.htm#P13_1345
[3]http://www.sec.gov/rules/final/33-7881.htm#P14_1382
[4]http://www.sec.gov/rules/final/33-7881.htm#P15_1468

public disclosure promptly. Under the regulation, the required public disclosure may be made by filing or furnishing a Form 8-K, or by another method or combination of methods that is reasonably designed to effect broad, non-exclusionary distribution of the information to the public.

Rule 10b5-1 addresses the issue of when insider trading liability arises in connection with a trader's "use" or "knowing possession" of material nonpublic information. This rule provides that a person trades "on the basis of" material nonpublic information when the person purchases or sells securities while aware of the information. However, the rule also sets forth several affirmative defenses, which we have modified in response to comments, to permit persons to trade in certain circumstances where it is clear that the information was not a factor in the decision to trade. Rule 10b5-2 addresses the issue of when a breach of a family or other non-business relationship may give rise to liability under the misappropriation theory of insider trading. The rule sets forth three non-exclusive bases for determining that a duty of trust or confidence was owed by a person receiving information, and will provide greater certainty and clarity on this unsettled issue.

### C.2.2 II. Selective Disclosure: Regulation FD

A. Background

As discussed in the Proposing Release[5], we have become increasingly concerned about the selective disclosure of material information by issuers. As reflected in recent publicized reports, many issuers are disclosing important nonpublic information, such as advance warnings of earnings results, to securities analysts or selected institutional investors or both, before making full disclosure of the same information to the general public. Where this has happened, those who were privy to the information beforehand were able to make a profit or avoid a loss at the expense of those kept in the dark.

[5] http://www.sec.gov/rules/final/33-7881.htm#P22_3881

We believe that the practice of selective disclosure leads to a loss of investor confidence in the integrity of our capital markets. Investors who see a security's price change dramatically and only later are given access to the information responsible for that move rightly question whether they are on a level playing field with market insiders.

Issuer selective disclosure bears a close resemblance in this regard to ordinary "tipping" and insider trading. In both cases, a privileged few gain an informational edge – and the ability to use that edge to profit – from their superior access to corporate insiders, rather than from their skill, acumen, or diligence. Likewise, selective disclosure has an adverse impact on market integrity that is similar to the adverse impact from illegal insider trading: investors lose confidence in the fairness of the markets when they know that other participants may exploit "unerodable informational advantages" derived not from hard work or insights, but from their access to corporate insiders[6]. The economic effects of the two practices are essentially the same. Yet, as a result of judicial interpretations, tipping and insider trading can be severely punished under the antifraud provisions of the federal securities laws, whereas the status of issuer selective disclosure has been considerably less clear.[7]

Regulation FD is also designed to address another threat to the integrity of our markets: the potential for corporate management to treat material information as a commodity to be used to gain or maintain favor with particular analysts or investors. As noted in the Proposing Release, in the absence of a prohibition on selective disclosure, analysts may feel pressured to report favorably about a company or otherwise slant their analysis in order to have continued access to selectively disclosed information. We are concerned, in this regard, with reports that analysts who publish negative views of an issuer are sometimes excluded by that issuer from calls and meetings to which other analysts are invited[8].

Finally, as we also observed in the Proposing Release, technological developments have

[6]http://www.sec.gov/rules/final/33-7881.htm#P25_5597
[7]http://www.sec.gov/rules/final/33-7881.htm#P26_6448
[8]http://www.sec.gov/rules/final/33-7881.htm#P28_7865

made it much easier for issuers to disseminate information broadly. Whereas issuers once may have had to rely on analysts to serve as information intermediaries, issuers now can use a variety of methods to communicate directly with the market. In addition to press releases, these methods include, among others, Internet webcasting and teleconferencing. Accordingly, technological limitations no longer provide an excuse for abiding the threats to market integrity that selective disclosure represents.

To address the problem of selective disclosure, we proposed Regulation FD. It targets the practice by establishing new requirements for full and fair disclosure by public companies.

Source: http://www.sec.gov/rules/final/33-7881.htm#P12_1307

Rule 100 – General Rule Regarding Selective Disclosure
Whenever an issuer, or any person acting on its behalf, discloses any material nonpublic information regarding that issuer or its securities to any person described in paragraph (b)(1) of this section, the issuer shall make public disclosure of that information as provided in Rule 101(e)[9].

Simultaneously, in the case of an intentional disclosure; and Promptly, in the case of a non-intentional disclosure. Except as provided in paragraph (b)(2) of this section, paragraph (a) of this section shall apply to a disclosure made to any person outside the issuer:

Who is a broker or dealer, or a person associated with a broker or dealer, as those terms are defined in Section 3(a)[10] of the Securities Exchange Act of 1934;

Who is an investment adviser, as that term is defined in Section 202(a)(11)[11] of the Investment Advisers Act of 1940; an institutional investment manager, as that term is defined in Section 13(f)(5)[12] of the Securities Exchange Act of 1934, that filed a report on Form 13F with the Commission for the most recent quarter ended prior to the date

[9] http://www.law.uc.edu/CCL/regFD/FD101.html#e
[10] http://www.law.uc.edu/CCL/34Act/sec3.html#a
[11] http://www.law.uc.edu/CCL/InvAdvAct/sec202.html
[12] http://www.law.uc.edu/CCL/34Act/sec13.html#f.5

of the disclosure; or a person associated with either of the foregoing. For purposes of this paragraph, a "person associated with an investment adviser or institutional investment manager" has the meaning set forth in Section 202(a)(17) of the Investment Advisers Act of 1940, assuming for these purposes that an institutional investment manager is an investment adviser;

Who is an investment company, as defined in Section 3[13] of the Investment Company Act of 1940, or who would be an investment company but for Section 3(c)(1) or Section 3(c)(7) thereof, or an affiliated person of either of the foregoing. For purposes of this paragraph, "affiliated person" means only those persons described in Section 2(a)(C)[14],(D), E), and (F) of the Investment Company Act of 1940, assuming for these purposes that a person who would be an investment company but for Section 3(c)(1) or Section 3(c)(7) of the Investment Company Act of 1940 is an investment company; or

Who is a holder of the issuer's securities, under circumstances in which it is reasonably foreseeable that the person will purchase or sell the issuer's securities on the basis of the information.

Paragraph (a) of this section shall not apply to a disclosure made:

To a person who owes a duty of trust or confidence to the issuer (such as an attorney, investment banker, or accountant);

To a person who expressly agrees to maintain the disclosed information in confidence;

To an entity whose primary business is the issuance of credit ratings, provided the information is disclosed solely for the purpose of developing a credit rating and the entity's ratings are publicly available; or

In connection with a securities offering registered under the Securities Act, other than an

[13]http://www.law.uc.edu/CCL/InvCoAct/sec3.html
[14]http://www.law.uc.edu/CCL/InvCoAct/sec2.html#a.3

offering of the type described in any of Rule 415(a)(1)(i) through (vi)[15] under the Securities Act (except an offering of the type described in Rule 415(a)(1)(i)[16] under the Securities Act also involving a registered offering, whether or not underwritten, for capital formation purposes for the account of the issuer (unless the issuers offering is being registered for the purpose of evading the requirements of this section)), if the disclosure is by any of the following means:

A registration statement filed under the Securities Act, including a prospectus contained therein;

A free writing prospectus used after filing of the registration statement for the offering or a communication falling within the exception to the definition of prospectus contained in clause (a) of section 2(a)(10) of the Securities Act; Any other Section 10(b) prospectus;

A notice permitted by Rule 135[17] under the Securities Act;

A communication permitted by Rule 134[18] under the Securities Act; or

An oral communication made in connection with the registered securities offering after filing of the registration statement for the offering under the Securities Act.

Source:

**Securities Lawyer's Deskbook**

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**http://www.law.uc.edu/CCL/regFD/FD100.html**

[15]http://www.law.uc.edu/CCL/33ActRls/rule415.html#a
[16]http://www.law.uc.edu/CCL/33ActRls/rule415.html#a.1.i
[17]http://www.law.uc.edu/CCL/33ActRls/rule135.html
[18]http://www.law.uc.edu/CCL/33ActRls/rule134.html

# APPENDIX D

## The Engle-Granger Methodology

The Engle-Granger methodology suffers from several drawbacks. The method essentially requires us to find the long-run equilibrium relationship between the integrated (assumed) series and then test whether the residuals from this regression are stationary. That is, if we have two non-stationary series $\{x_t\}$ and $\{y_t\}$ which we wish to test for cointegration, the long-run equilibrium relation of the type $y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$ is estimated. If the residual series $e_t$ obtained from the regression is stationary, then $\{x_t\}$ and $\{y_t\}$ are cointegrated of order (1, 1). However, the choice of which variable should be designated as independent or dependent introduces an element of arbitrariness. The problem is further exacerbated if there are three or more variables. For example, if we have three non-stationary series $\{x_t\}$, $\{y_t\}$ and $\{z_t\}$ then we can have the following long-run equilibrium relationships:

$$\begin{aligned} x_t &= \beta_0 + \beta_1 y_t + \beta_2 z_t + \varepsilon_{1t} \\ y_t &= \beta_3 + \beta_4 x_t + \beta_5 z_t + \varepsilon_{2t} \\ z_t &= \beta_6 + \beta_7 x_t + \beta_8 y_t + \varepsilon_{3t} \end{aligned} \tag{D.1}$$

Any of the three residual series would qualify for testing for a unit root. Moreover, there may be conflicting results, i.e., one residual series may indicate cointegration while others do not. Besides this, in the case of multiple cointegrating vectors, the Engle-Granger methodology does not provide a systematic procedure for estimating them separately. Also, the two-step procedure can carry over error from the first step to the next.

Johansen (1988) and Stock and Watson (1988) maximum likelihood estimators avoid the two-step procedure. If $\{X_t\}$ is an $n$x1 vector of I(1)variables and an autoregressive relationship exists such that
$X_t = \mu + A_1 X_{t-1} + A_2 X_{t-2} + \ldots + A_p X_{t-p} + \varepsilon_t$, it can be rewritten as
$\Delta X_t = \Pi X_{t-1} + \sum\limits_{i=1}^{p} \Gamma_i \Delta X_{t-1} + \varepsilon_t$
where $\Gamma_i = (k\text{x}k)$ coefficient matrix with elements $\Gamma_{jk}(i)t$,
with $\Pi = \sum\limits_{i=1}^{p} A_i - I$ and $\Gamma_i = -\sum\limits_{j=i+1}^{p} A_j$

The variables in $\{X_t\}$ are cointegrated if the rank of $\Pi$ is greater than zero. If $\Pi$ is not full rank, i.e., rank r $<$ n then two $n$ x $r$ matrices $\alpha$ and $\beta$ exist such that $\Pi = \alpha\beta'$ and $\beta' X_t$ is stationary. For a given r the maximum likelihood estimator of $\beta$ defines the combination of $X_t$ that gives the r largest canonical correlations of $\Delta X_t$ l and $X_{t-1}$. Johansen suggests testing these correlations with two likelihood ratio tests which in turn would be equivalent to testing the rank of $\Pi$. These are the Trace and Max Eigen Value tests. The two statistics are computed as

$$\begin{aligned} J_{trace} &= -T \sum_{i=r+1}^{n} \ln\left(1 - \hat{\lambda}_i\right) \\ J_{\max} &= -T \ln\left(1 - \hat{\lambda}_{r+1}\right) \end{aligned} \quad \text{(D.2)}$$

where $T$ is the sample size and $\hat{\lambda}_i$ is the $i^{th}$ largest canonical correlation.
The Trace Test tests the null hypothesis that there are $r$ cointegrating vectors against the alternative hypothesis that there are $n$ cointegrating vectors. The max Eigen Value Test instead tests that there are $r$ cointegrating vectors against the alternative hypothesis that there are $(r + 1)$ cointegrating vectors. There are some criticisms aimed at these tests also (see Perron and Campbell (**?**)). In particular, the Johansen procedure cannot distinguish nearly unit root variables and can overestimate the cointegrating rank.

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There is an extensive body of literature on the information share of markets particularly when a single asset or identical assets are traded in several markets. Most of these studies focus on the price discovery process and the information contribution of the individual markets. However the idea that the information share can be used as a measure of market integration (or fragmentation) has not been adequately explored. Regulatory and microstructure changes such as Fair Disclosure and Decimalization of tick-size have an effect on the information dissemination and price discovery. More efficient price discovery and greater information parity are some of the justifications offered for the introduction of such measures. This article measures the effects of such changes on the information share, the duration of impulse response functions, and tests whether such regulations have achieved greater informational parity and market integration.

ADVISOR'S APPROVAL: ______________________________