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Stock Market's Anticipation of Information and Reaction to the Release of Information

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Abstract

This study examines the stock market's anticipation of new information and reaction to the release of new information using U.S. daily returns for 2000 through 2011 after the adoption of Regulation Fair Disclosure in 2000. The empirical evidence presented supports the proportion that the stock market anticipates new information well before it is released and revises expectations in narrow windows near the release of the new information. The characteristics of the stock market's anticipation of new information and reaction to the release of new information depend on the type of firm and the state of the economy.

Keywords: Anticipation, Asset Pricing, Abnormal Return, Market Efficiency, Event Study, Advertising

JEL Classifications: G12, G14, M37

The growing competition for audience attention resulting from the proliferation of media alternatives has motivated firms to advertise during major television events (Chong, Filbeck, and Tompkins (2007); Filbeck, Zhao, Tompkins, and Chong (2009)). These firms are under increasing pressure to demonstrate the financial effectiveness of their advertising expenditures in terms of increases in shareholders' wealth (Chong, Filbeck, and Tompkins (2007); Johnston (2007); Filbeck, Zhao, Tompkins, and Chong (2009); Srinivasan and Hanssens (2009); Srinivasan, Pauwels, Silva-Risso, and Hanssens (2009); Rao and Bharadwaj (2008)). Previous research has shown that increasing or maintaining advertising expenditures has a positive effect on sales and net income (Kamber (2002)). Advertising during recessions has been shown to result in higher sales, market share, and earnings (Tellis and Tellis (2009)).

A major portion of many firms advertising budgets is spent on producing costly Super Bowl advertisements to improve or maintain sales and market share and focus media attention on the firm (Filbeck, Zhao, Tompkins, and Chong (2009); Thompson (2007)). Firms have traditionally measured the effectiveness of their Super Bowl advertisements by measuring viewers' familiarity with the advertisement, ability to recall information contained in the advertisement, and the likeability of the advertisement (Cacioppo and Petty (1979); Wu and Newell (2003)). Super Bowl advertisements provide new information about the future products, services, cash flows, and economic performance of the firm. Advertising during the Super Bowl is an investment that should provide an appropriate return to the shareholders (McAlister, Srinivasan, and Kim (2007)). Stock market participants must analyze the costs and benefits of the new information and determine the appropriate stock price (Filbeck, Zhao, Tompkins, and Chong (2009); Johnston (2010); Srinivasan and Hanssens (2009)). Previous research has shown that the traditional measures the effectiveness of advertising are not related in any consistent manner to the short-term stock price movements of advertisers around Super Bowls (Eastman, Iyer, and Wiggenhorn (2010); Kim and Morris (2003)).

I. Background

Event studies are designed to measure the stock price movements associated with a specific event that provides new information to the market participants (Chong, Filbeck, and Tompkins, (2007); Johnston, (2007)). Efficient market theory holds that when valuing stocks financial analysts and investors attempt to fully anticipate future events (Fama (1991 and 1998)). Persistent nonzero abnormal returns are inconsistent with market efficiency. Abnormal returns around an event date are indicators of the impact of the release of new information on shareholders' wealth. Event studies assume that a firm's stock price fully reflects all publicly available information (Filbeck, Zhao, Tompkins, and Chong (2009)). Market participants are assumed to react quickly and correctly when new information becomes available. Stock prices are assumed to fully reflect market participants' valuation of the firm. When a firm advertises during the Super Bowl, it provides new information to stock market participants. Abnormal returns occurring during an event window for the Super Bowl measure the effect of the new information provided by the advertisements (Filbeck, Zhao, Tompkins, and Chong (2009); Srinivasan and Hanssens (2009)). Positive abnormal returns during an event window indicate that the release of the new information is associated with an abnormal increase in shareholders' wealth and negative abnormal returns during an event window indicate that the release of the new information is associated with an abnormal decrease in shareholders' wealth.

The event study methodology was developed and is widely used in economics and finance (Kothari and Warner (2006)). A large literature in accounting, financial economics, and law and economics has used event study methods to examine the behavior of stock prices around important corporate events (Kothari (2001); Smith (1986); Jensen and Ruback (1983); Jensen and Warner (1988); Jarrell, Brickley, and Netter (1988)). Event studies have also been used widely in management and marketing. Announcements of new products, new product introductions, product recalls, product and market diversification announcements, product research and development, brand extension announcements, sponsorship of the Olympics, and name changes have been studies using the event study methodology (Chaney, Devinney, and Winer (1991); Lane and Jacobson (1995); Miyazaki and Morgan (2001); Farrell and Frame (1997); Johnston (2007)). Event studies have been used to measure the financial effects of advertising to enhance brand images, deceptive advertising, advertising to release new information, advertising financial relationships, advertising changes of slogans, advertising receipt of quality awards, changing advertising agencies, terminating advertising agencies, sponsorship of events, endorsements by celebrities, and advertising during Super Bowls (Clark, Cornwell, and Pruitt (2009); Johnston (2007); Johnston (2010); Kim and Morris (2003); Mathur, Mathur, and Rangan (1997); Miyazaki and Morgan (2001); Spais and Fillis (2006); Spais and Fillis (2008)).

Several studies have used event studies to examine the stock price movements of Super Bowl advertisers. The event study method often used in marketing research is presented by Miyazaki and Morgan (2001). Event windows are designed to capture the rapid responses of stock prices to the new information while limiting the effects of conflicting events and noise. When examining the effects of Super Bowl advertising, researchers have used event windows that run from five business days before to five business days after the Super Bowl (Johnston (2007); Eastman, Iyer, and Wiggenhorn (2010); Wiggenhorn, Eastman, Iyer, and Armul (2010)). Analysis of Super Bowls occurring from 1983 through 2001 found no significant average abnormal returns for advertisers (Fehle, Tsyplakov, and Zdorovtsov (2005)). Examination of abnormal returns for Super Bowls in 1998, 1999, and 2000 produced an overall average abnormal return of a negative two percent indicating that Super Bowl advertising is a costly form of ineffective investment (Kim and Morris (2003)). Negative abnormal returns have been reported for Super Bowl advertisers from 1998 through 2000 suggesting that Super Bowl advertising is associated with decreases in shareholders' wealth (Kim and Morris (2003)). Positive abnormal returns have been reported for Super Bowl advertisers from 1985 through 2005 suggesting that Super Bowl advertising is associated with increases in shareholders' wealth (Fehle, Tsyplakov, and Zdorovtsov (2005); Chang, Jiang, and Kim (2009)). A small positive statistically significant average one-day abnormal return and a negative average five-day abnormal was found for Super Bowl occurring from 1990 through 2005 (Chong, Filbeck, and Tompkins (2007)). One study examined whether the financial effects of Super Bowl advertising varies based on economic conditions by comparing the abnormal returns of Super Bowl advertisers for 2008 and 2009 and concluded that firms may need to reanalyze the financial effectiveness of their advertising expenditures during recessions (Wiggenhorn, Eastman, Iyer, and Armul (2010)). There is some evidence that abnormal returns may be affected by the state of the economy (Wiggenhorn, Eastman, Iyer, and Armul (2010); Tellis and Tellis (2009)). Previous research does not provide a consistent explanation of how stock price movements are associated with Super Bowl advertising.

This study examines the stock price movements associated with the release of new information after 2000 because the U.S. Securities and Exchange Commission approved Regulation Fair Disclosure on August 10, 2000. Accurate and timely information that satisfies the needs of all market participants is required by well-functioning, efficient, financial markets. Selective disclosure of important information to financial analysts and institutions makes the transparency and fairness of financial markets questionable. Regulation Fair Disclosure is designed to improve the flow of information to financial markets (Bailey, Li, Mao, and Zhong (2003)). By prohibiting selective disclosure and requiring broad, non-exclusionary disclosure of material information, it reduces the information disparities between individual and institutional investors. Parties are no longer able to trade legally on information obtained from selective disclosures.

This study examines the stock price movements associated with the release of new information for different phases of the business cycle because previous research has provided some empirical evidence that stock price movements for the release of new information may depend on the state of the economy (Wiggenhorn, Eastman, Iyer, and Armul (2010)). Dating for the peaks and troughs of U.S. business cycles is done by the National Bureau of Economic Research (NBER). The Business Cycle Dating Committee of the National Bureau of Economic Research (National Bureau of Economic Research (2012a)) maintains a chronology of the U.S. business cycle which is a list of alternating dates for peaks and troughs in economic activity that indicate when the direction of economic activity changes. The peak of the cycle is the last month before several key economic indicators such as output, employment, and retail sales begin to fall. The trough of the cycle refers to the last month before the same economic indicators begin to rise. The business cycle has two phases: the recession phases and the expansion phases. The recession phase is the period of time between a peak and a trough. The expansion phase is the time period between a trough and a peak. A significant decline in economic activity spreads across the economy during the recession phase. Economic activity rises substantially and widely during the expansion phase. The dating of peaks and troughs is somewhat subjective because key economic indicators often change direction at slightly different times. The Committee uses its definitions of recessions and expansions and applies judgment to identify brief reversals, recessions, and expansions. Although the term cycle is used, a business cycle is not a predictable, regular, or repeating phenomenon. There is little regularity in the duration and timing of the movements in economic activity.

The NBER's Business Cycle Dating Committee’s chronology of the U.S. business cycle indicates that three troughs and two peaks occurred from 2001 through 2011 (National Bureau of Economic Research (2012b)). A trough occurred in March of 1991. The ensuing expansion lasted for 120 months until March of 2001 when a peak occurred. The following recession lasted only 8 months until November of 2001 when a trough occurred. The next expansion lasted 73 months until December of 2007 when a peak occurred. The following recession lasted 18 months. A trough occurred in June of 2009. The economy has been in the expansion phase of the business cycle since June of 2009. The Dating Committee's chronology indicates that Super Bowls held in 2008 and 2009 occurred during a recession phase of the business cycle and all of the other Super Bowls from 2001 through 2011 occurred during expansion phases of the business cycle. The stock price movements for firms that advertised during Super Bowls occurring during the recession phase of the business cycle and firms that advertised during Super Bowls occurring during the expansion phase of the business cycle are examined.

This study examines the stock price movements associated with the release of new information for two different types of firms because event studies are designed to measure the stock price movements associated with a specific event that provides new information to the market participants and efficient market theory holds that when valuing stocks financial analysts and investors attempt to fully anticipate future events (Fama (1991 and 1998)). When firms have not advertised during the previous Super Bowl, stock market participants must learn over time that the firms will advertise during the next Super Bowl and attempt to fully anticipate the information to be released during the next Super Bowl and incorporated the effect of the anticipated information in the current price of the stock as the date for the release of the new information is approached. As the market participants learn more, the stock prices will reflect the market participants' valuation of the firm based on what is learned. When the actual new information is released, stock market participants will react quickly and revise their valuation of the firm based on the new information released by the advertisements. For firms that did not advertise during the previous Super Bowl, abnormal returns may occur during the estimation window long before the new information is released and also may occur during the event window when the information is released. When firms have advertised during the previous Super Bowl, stock market participants may be able to use prior information to anticipate the information to be released during the next Super Bowl and incorporated the effect of the anticipated information in the current price of the stock long before the new information is released during the current Super Bowl. The stock prices before the event window and long before the new information is released will fully reflect the market participants' valuation of the firm based on the anticipated information. When the actual new information is released, stock market participants will react quickly and revise their valuation of the firm based on the new information released by the advertisements. Abnormal returns may not occur during the estimation window but may occur during the event window for firms that advertised during the previous Super Bowl. This study examines the stock price movements for firms that did not advertise during the previous Super Bowl and for firms that did advertise during the previous Super Bowl. This study also examines the stock price movements and for firms that did not advertise during the previous Super Bowl and did advertise during a Super Bowl occurring during the recession phase of the business cycle, firms that did not advertise during the previous Super Bowl and did advertise during a Super Bowl occurring during the expansion phase of the business cycle, firms that did advertise during the previous Super Bowl and did advertise during a Super Bowl occurring during the recession phase of the business cycle, and firms that did advertise during the previous Super Bowl and did advertise during a Super Bowl occurring during the expansion phase of the business cycle.

II. Event Study Methodology

An event study is used to obtain empirical evidence on the stock market's anticipation of new information during the estimation window and reaction to the release of new information during the event window for firms that advertise during Super Bowls. Daily stock return data is used to obtain precise measures of abnormal returns. Event studies focus on measuring the average and cumulative average abnormal returns for a group of firms. Event studies are very powerful when abnormal performance is concentrated in the event window (Brown and Warner (1980 and 1985); MacKinlay (1997); Campbell, Lo, and MacKinlay (1997)). The actual stock return is thought of as being composed of two parts: a normal return and an abnormal return. The actual return on the stock for firm j for day t is generated by

$$R_{jt} = NR_{jt} + AR_{jt} \tag{1}$$

where R_{jt} is the actual daily return for firm j on day t, NR_{jt} is the normal return for firm j on day t, and AR_{jt} is the abnormal return for firm j on day t. t measures the relative day with respect to the event. The abnormal return is a direct measure of the abnormal change in the shareholders' wealth on day t associated with the event being studied. An asset pricing model for the normal return is estimated using data for an estimation window which precedes the event window and is used to calculate abnormal returns for an event window. Various asset pricing models have been used in the literature. A constant expected return model, the market-adjusted return model, the market model, the capital asset pricing model, and the Fama-French three factor model have been used for the normal return (Brown and Warner (1985); Campbell, Lo, and MacKinlay (1997); Fama and French (1992 and 1993)). The abnormal returns are calculated for different days in the event window by using

$$AR_{jt} = R_{jt} + NR_{jt} \tag{2}$$

where the normal return for firm j on day t is produced by using estimates for an asset pricing model.

An event study typically tries to determine if the cross-section of returns is significantly abnormal around the time of the event by focusing on the average abnormal return for a group of firms. The cross-sectional average abnormal return for a group of N firms for day t in the event window is calculated by using

$$AAR_t = \frac{1}{N}\sum_{j=1}^{N} AR_{jt} \tag{3}$$

If the new information released by an event is partially anticipated just before the event, part of the abnormal returns will appear before the event occurs. If the adjustment to the new information provided by the event is delayed a little, some of the abnormal returns will appear after the event. The degree to which an event is anticipated may differ because of coverage by outside parties and endogenous choices of the firm based on private information (Malatesta and Thompson (1985); Eckbo, Maksimovic, and Williams (1990)). Abnormal returns are aggregated over time to deal with partial anticipation and delayed response near the event. The cumulative abnormal return for firm j for the days in an event window starting with day t_1 and ending with day t_2 is calculated by using

$$CAR_{t_1 t_2} = \sum_{t=t_1}^{t_2} AR_{jt} \tag{4}$$

The cumulative average abnormal return for a group of firms for days in an event window running from t_1 to t_2 is calculated by using

$$CAAR_{t_1 t_2} = \sum_{t=t_1}^{t_2} AAR_{jt} \tag{5}$$

The Fama-French three factor model is used as the model for normal returns in this study because the finance literature has shown that it does an acceptable job of explaining rates of return (Fama and French (1992 and 1993); Brusa, Lee, and Liu (2011)). The power to detect abnormal returns is inversely related to the predictive power of the asset pricing model for normal returns. The traditional asset pricing model, the capital asset pricing model, uses only one factor (Sharpe (1964); Lintner (1965); Mossin (1966); Stone (1970)). Fama and French (1992) found that high value stocks (value stocks) outperform low value stocks (growth stocks) and small cap stocks outperform large cap stocks. The Fama-French three factor model is an asset pricing model designed to describe stock returns that extends the capital asset pricing model by adding a size factor and a value factor to the market risk factor. By including these two additional factors, the model adjusts for the abnormal performance tendencies of value stocks versus growth stocks and small cap stocks versus large cap stocks, which makes it a better predictive model for normal returns. Recent research has shown that the Fama-French three factor model also explains Monday returns (Brusa, Lee, and Liu (2011)).

When the Fama-French three factor model is used, actual returns for firm j are assumed to be generated by

$$R_{jt} = \alpha + RF_t + (RM_t - RF_t)\beta + SMB_t s + HML_t h + e_t \tag{6}$$

where α, β, s, and h are constants, RM_t is the daily rate of return for the market portfolio on day t, RF_t is the daily rate of return for the risk-free security on day t, SMB_t is the daily rate of return for the small size minus big size portfolio on day t, HML_t is the daily rate of return for the high value minus low value portfolio on day t, and e_t is an independent and identically distribution random variable with a mean of zero on day t. α measures the average daily abnormal return resulting from anticipation of the new information during the estimation window. The SMB factor measures the size premium investors receive by investing in stocks of companies with relatively small market capitalizations and short selling companies with relatively large market capitalizations. The SMB daily factor is computed as the average return for the 30 percent of total stocks with the smallest capitalization minus the average return for the 30 percent of total stocks with the largest capitalization. A positive SMB indicates that small cap stocks outperformed large cap stocks. A negative SMB indicates the large cap stocks outperformed small cap stocks. The HML factor measures the value premium investors receive by investing in stocks of companies with high book-to-market values (value stocks) and short selling stocks of companies with low book-to-market values (growth stocks). HML is computed as the average return for the 50 percent of stocks with the highest book-to-market values minus the average return of the 50 percent of stocks with the lowest book-to-market values. A positive HML indicates that value stocks outperformed growth stocks. A negative HML indicates that growth stocks outperformed value stocks. Daily data for the estimation period are used to estimate α, β, s, h, and the standard deviation of e_t. For the Fama-French three factor model, the normal return is given by

$$NR_{jt} = \alpha + RF_t + (RM_t - RF_t)\beta + SMB_t s + HML_t h \tag{7}$$

Different test statistics are often used to analyze abnormal returns in event studies. The standard deviation of the abnormal return is a key input required to calculate the test statistic for an event study. Since the power to detect abnormal returns is inversely related to the predictive power of the asset pricing model for the normal return, the Fama-French three factor should be able to identify abnormal returns better than the other models for the normal return. The Patell t statistic controls for the effect of stocks with large standard deviations by dividing the abnormal returns by the estimated standard deviation of the abnormal returns for the estimation period so that the abnormal returns are standardized (Patell (1976)). This study uses the Patell t statistic as one measure of the statistical significance of abnormal returns. The cross-sectional t statistic controls for event induced changes in the standard deviation of the abnormal returns by using the estimated standard deviation of the abnormal returns for the days being examined in the event period. This study uses the cross-sectional t statistic as another measure of the statistical significance of abnormal returns. The Boehmer, Musumeci, and Poulsen t statistic controls for both the effect of stocks with large standard deviations and event induced changes in the standard deviation by first dividing the abnormal returns by the estimated standard deviation of the abnormal returns for the estimation period and then using the estimated standard deviation of the standardized abnormal returns for the days being examined in the event period (Boehmer, Musumeci, and Poulsen (1991)). This study also uses the Boehmer, Musumeci, and Poulsen t statistic as a measure of the statistical significance of abnormal returns. The t statistic for the sign test assumes that one-half of the abnormal returns are positive. t-tests are used to determine the statistical significance of the average abnormal return and cumulative average abnormal return for a group of firms. Sign-tests are used to examine whether one-half of the abnormal returns and cumulative abnormal returns for a group of firms are positive.

III. Hypotheses

This study performs event studies to obtain empirical evidence on the stock market's anticipation of new information during the estimation window and reaction to the release of new information during the event window. Several hypotheses are examined in this study. Hypotheses 1 through 9 focus on the stock market's anticipation of new information during the estimation window and hypotheses 10 through 18 focus on the stock market's reaction to the release of new information during the event window. All hypotheses require two-tail tests.

Hypothesis 1: The stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements. The average abnormal return for firms advertising during the Super Bowls is zero in the estimation window prior to the Super Bowl. The alternative hypothesis is the average abnormal return for firms advertising during the Super Bowls is not zero in the estimation window prior to the Super Bowl.

Hypothesis 2: The stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle. The average abnormal return is zero in the estimation window prior to the Super Bowl for firms advertising during the Super Bowls occurring in the recession phase of the business cycle. The alternative hypothesis is the average abnormal return is not zero in the estimation window prior to the Super Bowl for firms advertising during the Super Bowls occurring in the recession phase of the business cycle.

Hypothesis 3: The stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle. The average abnormal return is zero in the estimation window prior to the Super Bowl for firms advertising during the Super Bowls occurring in the expansion phase of the business cycle. The alternative hypothesis is the average abnormal return is not zero in the estimation window prior to the Super Bowl for firms advertising during the Super Bowls occurring in the expansion phase of the business cycle.

Hypothesis 4: The stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements for firms that did not advertise during the previous Super Bowl. The average abnormal return is zero in the estimation window prior to the Super

Bowl for firms that advertise during the Super Bowl and did not advertise during the previous Super Bowl. The alternative hypothesis is the average abnormal return is not zero in the estimation window prior to the Super Bowl for firms that advertise during the Super Bowl and did not advertise during the previous Super Bowl.

Hypothesis 5: The stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements for firms that did advertise during the previous Super Bowl. The average abnormal return is zero in the estimation window prior to the Super Bowl for firms that advertise during the Super Bowl and did advertise during the previous Super Bowl. The alternative hypothesis is the average abnormal return is not zero in the estimation window prior to the Super Bowl for firms that advertise during the Super Bowl and did advertise during the previous Super Bowl.

Hypothesis 6: For firms that did not advertise during the previous Super Bowl, the stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle. For firms that did not advertise during the previous Super Bowl, the average abnormal return is zero in the estimation window prior to the Super Bowl for firms advertising during the Super Bowls occurring in the recession phase of the business cycle. The alternative hypothesis is for firms that did not advertise during the previous Super Bowl, the average abnormal return is not zero in the estimation window prior to the Super Bowl for firms advertising during the Super Bowls occurring in the recession phase of the business cycle.

Hypothesis 7: For firms that did not advertise during the previous Super Bowl, the stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle. For firms that did not advertise during the previous Super Bowl, the average abnormal return is zero in the estimation window prior to the Super Bowl for firms advertising during the Super Bowls occurring in the expansion phase of the business cycle. The alternative hypothesis is for firms that did not advertise during the previous Super Bowl, the average abnormal return is not zero in the estimation window prior to the Super Bowl for firms advertising during the Super Bowls occurring in the expansion phase of the business cycle.

Hypothesis 8: For firms that did advertise during the previous Super Bowl, the stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle. For firms that did advertise during the previous Super Bowl, the average abnormal return is zero in the estimation window prior to the Super Bowl for firms advertising during the Super Bowls occurring in the recession phase of the business cycle. The alternative hypothesis is for firms that did advertise during the previous Super Bowl, the average abnormal return is not zero in the estimation window prior to the Super Bowl for firms advertising during the Super Bowls occurring in the recession phase of the business cycle.

Hypothesis 9: For firms that did advertise during the previous Super Bowl, the stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle. For firms that did advertise during the previous Super Bowl, the average abnormal return is zero in the estimation window prior to the Super Bowl for firms advertising during the Super Bowls occurring in the expansion phase of the business cycle. The alternative hypothesis is for firms that did advertise during the previous Super Bowl, the average abnormal return is not zero in the estimation window prior to the Super Bowl for firms advertising during the Super Bowls occurring in the expansion phase of the business cycle.

Hypothesis 10: The stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements. The average abnormal return for firms advertising during the Super Bowls is zero in the event window for the Super Bowl. The alternative hypothesis is the average abnormal return for firms advertising during the Super Bowls is not zero in the event window for the Super Bowl.

Hypothesis 11: The stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle. The average abnormal return is zero in the event window for the Super Bowl for firms advertising during the Super Bowls occurring in the recession phase of the business cycle. The alternative hypothesis is the average abnormal return is not zero in the event window for the Super Bowl for firms advertising during the Super Bowls occurring in the recession phase of the business cycle.

Hypothesis 12: The stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle. The average abnormal return is zero in the event window for the Super Bowl for firms advertising during the Super Bowls occurring in the expansion phase of the business cycle. The alternative hypothesis is the average abnormal return is not zero in the event window for the Super Bowl for firms advertising during the Super Bowls occurring in the expansion phase of the business cycle.

Hypothesis 13: The stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements for firms that did not advertise during the previous Super Bowl. The average abnormal return is zero in the event window for the Super Bowl for firms that did advertise during the Super Bowl and did not advertise during the previous Super Bowl. The alternative hypothesis is the average abnormal return is not zero in the event window for the Super Bowl for firms that did advertise during the Super Bowl and did not advertise during the previous Super Bowl.

Hypothesis 14: The stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements for firms that did advertise during the previous Super Bowl. The average abnormal return is zero in the event window for the Super Bowl for firms those advertise during the Super Bowl and did advertise during the previous Super Bowl. The alternative hypothesis is the average abnormal return is not zero in the event window for the Super Bowl for firms that did advertise during the Super Bowl and did advertise during the previous Super Bowl.

Hypothesis 15: For firms that did not advertise during the previous Super Bowl, the stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle. For firms that did not advertise during the previous Super Bowl, the average abnormal return is zero in the event window for the Super Bowl for firms advertising during the Super Bowls occurring in the recession phase of the business cycle. The alternative hypothesis is for firms that did not advertise during the previous Super Bowl, the average abnormal return is not zero in the event window for the Super Bowl for firms advertising during the Super Bowls occurring in the recession phase of the business cycle.

Hypothesis 16: For firms that did not advertise during the previous Super Bowl, the stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle. For firms that did not advertise during the previous Super Bowl, the average abnormal return is zero in the event window for the Super Bowl for firms advertising during the Super Bowls occurring in the expansion phase of the business cycle. The alternative hypothesis is for firms that did not advertise during the previous Super Bowl, the average abnormal return is not zero in the event window for the Super Bowl for firms advertising during the Super Bowls occurring in the expansion phase of the business cycle.

Hypothesis 17: For firms that did advertise during the previous Super Bowl, the stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle. For firms that did advertise during the previous Super Bowl, the average abnormal return is zero in the event window for the Super Bowl for firms advertising during the Super Bowls occurring in the recession phase of the business cycle. The alternative hypothesis is for firms that did advertise during the previous Super Bowl, the average abnormal return is not zero in the event window for the Super Bowl for firms advertising during the Super Bowls occurring in the recession phase of the business cycle.

Hypothesis 18: For firms that did advertise during the previous Super Bowl, the stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle. For firms that did advertise during the previous Super Bowl, the average abnormal return is zero in the event window for the Super Bowl for firms advertising during the Super Bowls occurring in the expansion phase of the business cycle. The alternative hypothesis is for firms that did advertise during the previous Super Bowl, the average abnormal return is not zero in the event window for the Super Bowl for firms advertising during the Super Bowls occurring in the expansion phase of the business cycle.

IV. Data and Results

This study examines stock prices movements of Super Bowl advertisers after the adoption of Regulation Fair Disclosure in August of 2000. The identities of firms advertising during Super Bowls were obtained from *Advertising Age* and *USA Today*. Daily rates of return for the firms are obtained from Wharton Research Data Services. Firms with incomplete information or conflicting events were eliminated from the sample. There are 198 observations in the final sample for Super Bowls occurring from 2001 through 2011. Thirty-seven observations are firms that advertised during Super Bowls occurring during the recession phase of the business cycle and 161 observations are for firms that advertised during Super Bowls occurring during expansion phases of the business cycle. Eighty-eight observations are for firms that did not advertise during the previous Super Bowl. One hundred and eleven observations are for firms that did advertise during the previous Super Bowl. Sixteen observations are for firms that did not advertise during the previous Super Bowl and advertised during Super Bowls occurring during the recession phase of the business cycle. Seventy-two observations are for firms that did not advertise during the previous Super Bowl and advertised during Super Bowls occurring during expansion phases of the business cycle. Twenty-one observations are for firms that did advertise during the previous Super Bowl and advertised during Super Bowls occurring during the recession phase of the business cycle. Eighty-nine observations are for firms that did advertise during the previous Super Bowl and advertised during Super Bowls occurring during expansion phases of the business cycle. Data for the daily risk-free rates of return, daily market rates of return, daily rates of return for the SMB portfolio, and daily rates of return for the HML portfolio are obtained from Ken French's website. The parameters of the Fama-French three factor model are estimated for each firm using an estimation window beginning 231 business days and ending 31 business days before the Super Bowl. The estimated models for normal returns are used to calculate abnormal returns for each firm using an event window beginning two business days before and ending one business day after the Super Bowl.

Tables 1 through 4 provide results for the stock market's anticipation of new information during the estimation window and tables 5 through 8 provide results for the stock market's reaction to the release of new information during the event window. Tables 1 through 4 show the average daily abnormal returns for 2001 through 2011 occurring during the estimation window prior to the Super Bowl. The average daily abnormal return occurring during the estimation window prior to the Super Bowl is the measure for the anticipation of new information used in this study. A positive average daily abnormal return indicates that a firm's capital gains yield is higher than normal. A negative average daily abnormal return indicates that a firm's capital gains yield is lower than normal. Tables 5 through 8 show the cumulative average abnormal returns for the three days for 2001 through 2011 occurring during the event window. The cumulative average abnormal return occurring during the event window for the Super Bowl is the measure for the stock market's reaction to the release of new information used in this study. A positive cumulative average abnormal return indicates that a firm's capital gains yield is higher than normal. A negative cumulative average abnormal return indicates that a firm's capital gains yield is lower than normal. Tables 1 through 8 also show the Patell t statistic, the cross-sectional t statistic, the Boehmer et al. t statistic, the percent positive, and the sign-test t statistic. t statistics that are significantly different from zero are in bold font with asterisks indicating their levels of significance.

Table I: Average daily abnormal returns for 2001 through 2011

Estimation window	Number of events in portfolio	Average abnormal return (%)	Patell t statistic	Cross-sectional t statistic	Boehmer et al. t statistic	Percent positive	Sign-test t statistic
(-231,-31)	198	0.0140	1.6257	1.4393	**1.6856***	58.08	**2.2741*****

Numbers in bold type are significant at the 0.10, 0.05, 0.025, and 0.01 levels for two-tail tests. One asterisk indicates the 0.10 level, two asterisks indicate the 0.05 level, three asterisks indicate the 0.025 level, and four asterisks indicate the 0.01 level.

Table I shows the average daily abnormal returns for the estimation window running from 231 business days before through 31 business days before the Super Bowl for all firms advertising during Super Bowls occurring from 2001 through 2011. The average daily abnormal return and t statistics are provided for all 198 firms in the study. The average daily abnormal return of 0.0140 percent is significantly different from zero at the 0.10 level for a two-tail test. Hypothesis 1, stating stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements, is rejected at the 0.10 level of significance. This indicates that on average for all firms the anticipation of new information that will be provided by the Super Bowl advertisements produces average capital gains yields that are 5.11 percent higher than normal when annualized using the simple interest model and 365 days.

Table II: Average daily abnormal returns for 2001 through 2011 by state of the economy

Estimation window	State of economy	Number of events in portfolio	Average abnormal return (%)	Patell t statistic	Cross-sectional t statistic	Boehmer et al. t statistic	Percent positive	Sign-test t statistic
(-231,-31)	Recession	37	-0.0130	-0.3716	-0.5780	-0.3124	51.35	0.1644
	Expansion	161	0.0201	**1.9809****	**1.8797***	**2.1901****	59.63	**2.4443*****

Numbers in bold type are significant at the 0.10, 0.05, 0.025, and 0.01 levels for two-tail tests. One asterisk indicates the 0.10 level, two asterisks indicate the 0.05 level, three asterisks indicate the 0.025 level, and four asterisks indicate the 0.01 level.

Average daily abnormal returns for the estimation window running from 231 business days before through 31 business days before the Super Bowl for firms advertising during Super Bowls occurring in the recession phase of the business cycle and for firms advertising during Super Bowls occurring in the expansion phase of the business cycle are shown separately in Table II. The average daily abnormal return and t statistics for the 37 firms in the study that advertised during Super Bowls occurring in the recession phase of the business cycle are shown in Table II. The average daily abnormal return of -0.0130 percent is not significantly different from zero. Hypothesis 2, stating that stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle, is not rejected. This indicates that on average for firms advertising during the recession phase the anticipation of new information does not produce abnormal average capital gains yields. Table II also shows the average daily abnormal return and t statistics for the 161 firms in the study that advertised during Super Bowls occurring in the expansion phase of the business cycle. The average daily abnormal return of 0.0201 percent is significantly different from zero at the 0.05 level. Hypothesis 3, stating that stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle, is rejected at the 0.05 level of significance. This indicates that on average for firms advertising during the expansion phase the anticipation of new information that will be provided by the Super Bowl advertisements produces average capital gains yields that are 7.3365 percent higher than normal when annualized using the simple interest model and 365 days.

Table III: Average daily abnormal returns for 2001 through 2011 by type of firm

Estimation window	Type of firm	Number of events in portfolio	Average abnormal return (%)	Patell t statistic	Cross-sectional t statistic	Boehmer et al. t statistic	Percent positive	Sign-test t statistic
(-231,-31)	Did not	88	0.0245	**1.9321***	1.6247	**1.9258***	57.96	1.4924
	Did	110	0.0055	0.4529	0.4376	0.4867	58.18	**1.7162***

Numbers in bold type are significant at the 0.10, 0.05, 0.025, and 0.01 levels for two-tail tests. One asterisk indicates the 0.10 level, two asterisks indicate the 0.05 level, three asterisks indicate the 0.025 level, and four asterisks indicate the 0.01 level.

Table III shows the average daily abnormal return and t statistics for the 88 firms in the study that advertised during the Super Bowls and did not advertise during the previous Super Bowl.

The average daily abnormal return of 0.0245 percent is significantly different from zero at the 0.10 level. Hypothesis 4, stating that stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements for firms that did not advertise during the previous Super Bowl, is rejected at the 0.10 level of significance for a two-tail test. This indicates that on average for firms that did not advertise during the previous Super Bowl the anticipation of new information that will be provided by the Super Bowl advertisements produces average capital gains yields that are 8.9425 percent higher than normal when annualized using the simple interest model and 365 days. Table III also shows the average daily abnormal return and t statistics for the 110 firms in the study that advertised during Super Bowls and did advertise during the previous Super Bowl. The average daily abnormal return of 0.0055 percent is not significantly different from zero. Hypothesis 5, stating stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements for firms that did advertise during the previous Super Bowl, is not rejected. This indicates that on average for firms advertising during the Super Bowl that did advertise during the previous Super Bowl the anticipation of new information does not produce average capital gains yields that are abnormal.

Table IV: Average daily abnormal returns for 2001 through 2011 by type of firm and state of economy

Estimation window	State of economy and type of firm	Number of events in portfolio	Average abnormal return (%)	Patell t statistic	Cross-sectional t statistic	Boehmer et al. t statistic	Percent positive	Sign-test t statistic
(-231,-31)	Did not, recession	16	0.0021	0.4039	0.0604	0.3497	43.75	-0.5000
	Did not, expansion	72	0.0295	**2.3265*****	**1.7591***	**2.4179*****	61.11	**1.8856****
	Did, recession	21	-0.0245	-0.1407	-0.8248	-0.1132	57.14	0.6547
	Did, expansion	89	0.0126	0.5718	0.9069	0.6739	58.43	1.5900

Numbers in bold type are significant at the 0.10, 0.05, 0.025, and 0.01 levels for two-tail tests. One asterisk indicates the 0.10 level, two asterisks indicate the 0.05 level, three asterisks indicate the 0.025 level, and four asterisks indicate the 0.01 level.

Table IV shows the average daily abnormal return and t statistics for the 16 firms in the study that advertised during Super Bowls occurring during the recession phase of the business cycle and did not advertise during the previous Super Bowl. The average daily abnormal return of 0.0021 percent is not significantly different from zero. Hypothesis 6, stating that for firms that did not advertise during the previous Super Bowl, the stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle, is not rejected. This indicates that on average for firms that did not advertise during the previous Super Bowl and advertised during a Super Bowl occurring during the recession phase stock prices the anticipation of new information does not produce abnormal average capital gains yields. The average daily abnormal return and t statistics for the 72 firms in the study that advertised during Super Bowls occurring during the expansion phase of the business cycle and did advertise during the previous Super Bowl are also shown in Table IV. The average daily abnormal return of 0.0295 percent is significantly different from zero at the 0.025 level. Hypothesis 7, stating for firms that did not advertise during the previous Super Bowl, the stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle, is rejected at the 0.025 level of significance for a two-tail test. This indicates that on average for firms that did not advertise during the previous Super Bowl and advertised during a Super Bowl occurring during the expansion phase the anticipation of new information that will be provided by the Super Bowl advertisements produces average capital gains yields that are 10.7675 percent higher than normal when annualized using the simple interest model and 365 days.

Table IV shows the average daily abnormal return and t statistics for the 21 firms in the study that advertised during Super Bowls occurring during the recession phase of the business cycle and did advertise during the previous Super Bowl. The average daily abnormal return of -0.0245 percent is not significantly different from zero. Hypothesis 8, stating for firms that did advertise during the previous Super Bowl, the stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle, is not rejected. This indicates that on average for firms that did advertise during the previous Super Bowl and advertised during a Super Bowl occurring during the recession phase the anticipation of new information does not produce average capital gains yields that are abnormal. The average daily abnormal return and t statistics for the 89 firms in the study that advertised during Super Bowls occurring during the expansion phase of the business cycle and did advertise during the previous Super Bowl are also shown in Table IV. The average daily abnormal return of 0.0126 percent is not significantly different from zero. Hypothesis 9, stating for firms that did advertise during the previous Super Bowl, the stock market participants do not anticipate the information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle, is not rejected. This indicates that on average for firms that did not advertise during the previous Super Bowl and advertised during a Super Bowl occurring during the expansion phase the anticipation of new information does not produce abnormal average capital gains yields.

Table V: Cumulative average abnormal returns for three days for 2001 through 2011

Event window	Number of events in portfolio	Cumulative average abnormal return (%)	Patell t statistic	Cross-sectional t statistic	Boehmer et al. t statistic	Percent positive	Sign-test t statistic
(-2,1)	198	-0.5956	**-2.0176****	**-1.8843***	**-1.7189***	46.47	-0.9949

Numbers in bold type are significant at the 0.10, 0.05, 0.025, and 0.01 levels for two-tail tests. One asterisk indicates the 0.10 level, two asterisks indicate the 0.05 level, three asterisks indicate the 0.025 level, and four asterisks indicate the 0.01 level.

Table V shows the cumulative average abnormal returns for an event window running from two business days before through one business day after the Super Bowl for all firms advertising during Super Bowls occurring from 2001 through 2011. The cumulative average abnormal return and t statistics are provided for all 198 firms in the study. The cumulative average abnormal return of -0.5956 percent is significantly different from zero at the 0.05 level for a two-tail test. Hypothesis 10, stating that stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements, is rejected at the 0.05 level of significance. This indicates that on average for all firms stock prices react negatively to the release of the new information provided by the advertisements and capital gains yields are 0.5956 percent lower than normal for these three days.

Table VI: Cumulative average abnormal returns for three days for 2001 through 2011 by state of the economy

Event window	Business cycle phase	Number of events in portfolio	Cumulative average abnormal return (%)	Patell t statistic	Cross-sectional t statistic	Boehmer et al. t statistic	Percent positive	Sign-test t statistic
(-2,1)	Recession	37	-2.1867	**-3.1625******	**-2.1331****	**-2.1634****	32.43	**-2.1372****
	Expansion	161	-0.2299	-0.7214	-0.7561	-0.6654	49.69	-0.0788

Numbers in bold type are significant at the 0.10, 0.05, 0.025, and 0.01 levels for two-tail tests. One asterisk indicates the 0.10 level, two asterisks indicate the 0.05 level, three asterisks indicate the 0.025 level, and four asterisks indicate the 0.01 level.

Cumulative average abnormal returns for an event window running from two business days before through one business day after the Super Bowl for firms advertising during Super Bowls occurring in the recession phase of the business cycle and for firms advertising during Super Bowls occurring in the expansion phase of the business cycle are shown separately in Table VI. The cumulative average abnormal return and t statistics for the 37 firms in the study that advertised during Super Bowls occurring in the recession phase of the business cycle are provided in Table VI. The cumulative average abnormal return of -2.1867 percent is significantly different from zero at the 0.01 level for a two-tail test. Hypothesis 11, stating that stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle, is rejected at the 0.01 level of significance. This indicates that on average for firms advertising during the recession phase stock prices react negatively to the release of the new information provided by the advertisements and capital gains yields are 2.1867 percent lower than normal for these three days. Table VI also shows the cumulative average abnormal return and t statistics for the 161 firms in the study that advertised during Super Bowls occurring in the expansion phase of the business cycle. The cumulative average abnormal return of -0.2299 percent is not significantly different from zero. Hypothesis 12, stating that stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle, is not rejected. This indicates that on average for firms advertising during the expansion phase stock prices do not react to the release of the new information provided by the advertisements.

Table VII: Cumulative average abnormal returns for three days for 2001 through 2011 by type of firm

Event window	Type of firm	Number of events in portfolio	Cumulative average abnormal return (%)	Patell t statistic	Cross-sectional t statistic	Boehmer et al. t statistic	Percent positive	Sign-test t statistic
(-2,1)	Did not	88	-0.0065	-0.2456	-0.0154	-0.2380	53.41	0.6396
	Did	110	-1.0668	**-2.4872*****	**-2.3498*****	**-1.9539***	40.91	**-1.9069***

Numbers in bold type are significant at the 0.10, 0.05, 0.025, and 0.01 levels for two-tail tests. One asterisk indicates the 0.10 level, two asterisks indicate the 0.05 level, three asterisks indicate the 0.025 level, and four asterisks indicate the 0.01 level.

Table VII shows the cumulative average abnormal return and t statistics for the 88 firms in the study that advertised during the Super Bowls and did not advertise during the previous Super Bowl. The cumulative average abnormal return of -0.0065 percent is not significantly different from zero. Hypothesis 13, stating that stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements for firms that did not advertise during the previous Super Bowl, is not rejected. This indicates that on average for firms that did not advertise during the previous Super Bowl stock prices do not react to the release of the new information provided by the advertisements. Table VII also shows the cumulative average abnormal return and t statistics for the 110 firms in the study that advertised during the Super Bowls and did advertise during the previous Super Bowl. The cumulative average abnormal return of -1.0668 percent is significantly different from zero at the 0.025 level. Hypothesis 14, stating that stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements for firms that did advertise during the previous Super Bowl, is rejected at the 0.025 level of significance. This indicates that on average for firms advertising during the Super Bowl that did advertise during the previous Super Bowl stock prices react negatively to the release of the new information provided by the advertisements and capital gains yields are 1.0668 percent lower than normal for these three days.

Table VIII: Cumulative average abnormal returns for three days for 2001 through 2011 by type of firm and state of the economy

Event window	Type of firm	Number of events in portfolio	Cumulative average abnormal return (%)	Patell t statistic	Cross-sectional t statistic	Boehmer et al. t statistic	Percent positive	Sign-test t statistic
(-2,1)	Did not, recession	16	-0.8170	-0.9860	-0.5197	-0.7035	43.75	-0.5000
	Did not, expansion	72	0.1736	0.1933	0.4491	0.2065	55.56	0.9428
	Did, recession	21	-3.2302	**-3.3372******	**-2.4115*****	**-2.2160****	23.81	**-2.4004****
	Did, expansion	89	-0.5563	-1.1441	-1.2323	-0.9599	44.94	-0.9540

Numbers in bold type are significant at the 0.10, 0.05, 0.025, and 0.01 levels for two-tail tests. One asterisk indicates the 0.10 level, two asterisks indicate the 0.05 level, three asterisks indicate the 0.025 level, and four asterisks indicate the 0.01 level.

Table VIII shows the cumulative average abnormal return and t statistics for the 16 firms in the study that advertised during Super Bowls occurring during the recession phase of the business cycle and did not advertise during the previous Super Bowl. The cumulative average abnormal return of -0.8170 percent is not significantly different from zero. Hypothesis 15, stating that for firms that did not advertise during the previous Super Bowl, the stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle, is not rejected. This indicates that on average for firms that did not advertise during the previous Super Bowl and advertised during a Super Bowl occurring during the recession phase stock prices do not react to the release of the new information provided by the advertisements. The cumulative average abnormal return and t statistics for the 72 firms in the study that advertised during Super Bowls occurring during the expansion phase of the business cycle and did advertise during the previous Super Bowl are also shown in Table VIII. The cumulative average abnormal return of 0.1736 percent is not significantly different from zero. Hypothesis 16, stating that for firms that did not advertise during the previous Super Bowl, the stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle, is not rejected. This indicates that on average for firms that did not advertise during the previous Super Bowl and advertised during a Super Bowl occurring during the expansion phase stock prices do not react to the release of the new information provided by the advertisements.

Table VIII shows the cumulative average abnormal return and t statistics for the 21 firms in the study that advertised during Super Bowls occurring during the recession phase of the business cycle and did advertise during the previous Super Bowl. The cumulative average abnormal return of -3.2302 percent is significantly different from zero at the 0.01 level of significance for a two-tail test. Hypothesis 17, stating that for firms that did advertise during the previous Super Bowl, the stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle, is rejected at the 0.01 level of significance. This indicates that on average for firms that did advertise during the previous Super Bowl and advertised during a Super Bowl occurring during the recession phase stock prices react negatively to the release of the new information provided by the advertisements and capital gains yields are 3.2302 percent lower than normal for these three days. The cumulative average abnormal return and t statistics for the 89 firms in the study that advertised during Super Bowls occurring during the expansion phase of the business cycle and did advertise during the previous Super Bowl are also shown in Table VIII. The cumulative average abnormal return of -0.5563 percent is not significantly different from zero. Hypothesis 18, stating that for firms that did advertise during the previous Super Bowl, the stock prices prior to the Super Bowl fully reflect all information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle, is not rejected. This indicates that on average for firms that did not advertise during the previous Super Bowl and advertised during a Super Bowl occurring during the expansion phase stock prices do not react to the release of the new information provided by the advertisements.

The results for anticipation and reaction effects are robust with respect to the asset pricing model used for normal returns and to firm-specific control variables. The abnormal returns remain essentially the same when the Carhart (1997) momentum term is added to the Fama-French three factor model as a fourth factor in the model used for normal returns. The firm-specific control variables examined were market capitalization, advertising expense to net sales of the advertiser, and the ad meter effectiveness/creativity ratings from *USA Today*. Analysis of these firm-specific control indicated they are significantly related to abnormal returns for the anticipation and react effects.

V. Summary and Conclusions

The average daily abnormal return occurring during the estimation window prior to the Super Bowl is the measure for anticipation of new information used in this study. Overall, the stock market participants anticipate the information that will be provided by the Super Bowl advertisements. This produces an average abnormal return of 5.11 percent when annualized using the simple interest model and 365 days. Stock market participants anticipate the information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle. This produces an average abnormal return of 7.3365 when annualized using the simple interest model and 365 days. Stock market participants anticipate the information that will be provided by the Super Bowl advertisements for firms that did not advertise during the previous Super Bowl producing an average abnormal return of 8.9425 percent when annualized using the simple interest model and 365 days. For firms that did not advertise during the previous Super Bowl, the stock market participants anticipate the information that will be provided by the Super Bowl advertisements occurring during the expansion phase of the business cycle. This produces an average abnormal return of 10.7675 percent when annualized using the simple interest model and 365 days. Firms that did not advertise during the previous Super Bowl and advertised during a Super Bowl occurring during the expansion phase of the business cycle are the source of the abnormally large positive average abnormal return for the anticipation of the new information.

The cumulative average abnormal return occurring during the event window for the Super Bowl is the measure for the reaction to the release of new information used in this study. Overall, the stock prices prior to the Super Bowl do not fully reflect all information that will be provided by the Super Bowl advertisements. The cumulative average abnormal return for the event is -0.5956 percent. The stock prices prior to the Super Bowl do not fully reflect all information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle. The cumulative average abnormal return for the event window for firms advertising during the recession phase is -2.1867 percent. The stock prices prior to the Super Bowl do not fully reflect all information that will be provided by the Super Bowl advertisements for firms that did advertise during the previous Super Bowl. The cumulative average abnormal return for the event window for firms that did advertise during the previous Super Bowl is -1.0668 percent. For firms that did advertise during the previous Super Bowl, the stock prices prior to the Super Bowl does not fully reflect all information that will be provided by the Super Bowl advertisements occurring during the recession phase of the business cycle. The cumulative average abnormal return for the event window is -3.2302 percent firms that advertised during the previous Super Bowl and advertised during a Super Bowl occurring during the recession phase. Firms that advertised during the previous Super Bowl and advertise during a Super Bowl occurring during the recession phase of the business cycle are the source of the abnormally large negative cumulative average abnormal returns for the reaction to the release of new information.

The anticipation of new information results in an average abnormal return that is 10.7675 percent higher than normal when annualized using the simple interest model and 365 days. This is produced by firms that did not advertise during the previous Super Bowl and advertise during a Super Bowl occurring during the expansion phase of the business cycle. Firms that advertised during the previous Super Bowl and advertise during a Super Bowl occurring during the recession phase of the business cycle are the source of the abnormally large negative cumulative average abnormal returns for the reaction to the release of new information. The reaction to the release of new information results in a cumulative average abnormal return of -3.2302 percent. This is produced by firms that advertised during the previous Super Bowl and advertise during a Super Bowl occurring during the recession phase of the business cycle.

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Cointegration Analysis of the Effect of Decimalization on Market Equilibrium and Price Discovery

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Abstract

Recent crises have focused interest on methods to improve the functioning of financial markets. In this context it would be prudent to evaluate the effects of previous changes. Previous research on decimalization of tick size, a significant microstructure change, mostly examines its effects on spreads etc. This paper studies the effect of decimalization on the dynamics of market equilibrium in fragmented markets, when single or identical assets are traded in several markets. Using cointegration analysis this study finds that when a price innovation enters one market, the time taken for new equilibrium to be reached by other markets is significantly longer after decimalization. This finding is important in the context of the current market environment of Direct Market Access (DMA). When markets are in disequilibrium even for a few additional micro seconds, high frequency trading algorithms can provide a trading advantage, and create new arbitrage opportunities.

Optimal allocation of limited resources is a crucial challenge for any economy. In developed markets, efficient transference of capital is achieved through financial securities and a market microstructure design that accurately discovers the prices of these securities. This would require financial markets not hindered by structural flaws. An important question then is what affects the dissemination of information and price discovery. Over time, the number of markets has increased giving investors greater choice of trading venues. These different markets introduce new information and thus contribute to price discovery. To facilitate trade, each market sets its own rules of exchange. For the most part these rules, that is, the microstructure, like the minimum tick-size, are arbitrary and have evolved from the exigencies of actual trade. These rules influence the introduction and impounding of new information into prices as well as the dissemination of information through markets in a fundamental way. Any changes to the microstructure of markets will have an effect on efficient functioning of markets. Clearly, an important, yet less explored line of inquiry is how microstructure affects the interactions of various markets and how such effects are manifested in price discovery.

The recent financial crises have refocused interest in structural reform of financial markets. Research has endeavored to identify the market imperfections that may justify changes. However, it is necessary to proceed with caution. Indiscriminate changes, far from achieving the desired results, could further exacerbate the crisis. It is therefore imperative that the effect of previous changes be studied. At the very least it would throw some light on the issue of whether existing structures have increased efficiency and what changes need to be instituted. The motivation for this paper is provide an answer to some of these questions and perhaps to address some of the gaps in existing literature pertaining to these issues.

The effect of decimalization on the spread and its components such as, liquidity, volatility, transaction costs etc has been well documented. However the issue of how it affects information flow and market equilibrium 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 therefore there is lesser incentive for information discovery. However narrow spreads increase the probability of the efficient price being outside the spread and provides an opportunity for profitable trading. Another effect of smaller tick size is that small amounts of new information could cause the price to shift. E.g. if the tick size was an eighth (12.5 cents), new information that shifts the efficient price by only two or three cents cannot be incorporated into the price since the minimum tick is much larger than the new information. The price will remain at the current level even with new information available. The price would shift only when the new information accumulates to a level equal or larger than the current tick size. But with decimalization relatively small amounts of new information can immediately be incorporated into prices. The effect of narrower spreads and the ability to incorporate smaller amounts of information increases the incentive to discover information. This potential for greater trading opportunities would encourage not just the traders in large venues, but also smaller traders in the satellite markets to indulge in price discovery, thus increasing the information contributions of the satellite venues. The rest of the paper is organized as follows. Section I briefly describes microstructure and information flow. Section II reviews the literature on price discovery, tick size and develops the hypotheses. The methodology and estimation are described in Section III and Section IV discusses the results. Section V concludes. A brief review of cointegration is provided in the appendix.

I. 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 how disequilibrium is corrected, is not considered. Classical economics views the market as a monolithic trading space. 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. The practical exigencies of trading require some structure to be imposed upon the market, i.e. some rules or agreements governing the exchange process need to be instituted. Quantities and prices cannot be continuous neither can markets operate ceaselessly. Therefore rules specifying the discreteness of quantities, minimum price changes, and market operating times need to be determined. Besides this, adequate channels for the communication and dissemination of information need to be created in order to ensure that markets are informationally efficient and securities prices reflect all available information. These constitute the rules or the structure of the market, and will in influence the path of price evolution. This is the field of market microstructure. An important departure of the microstructure setting from the classical setting of trade is that it is neither unconstrained nor costless. The original random walk characterization of securities prices may seem inappropriate. But prices are determined to a significant extant by the participants' conditional expectation sequences which can be characterized as some evolving process subjected to zero-mean disturbances. Therefore the observed price may be modeled as a random walk component, to which a trade effect is added. The random walk, being a martingale, could be interpreted as the efficient price in the classical economic sense; however the difficulty is that it is unobservable. Central to the classical treatment of market microstructure is the concept of an asset trading in single homogenous market. The operations of the participants provide an inflow of information into the market which is impounded into the price of the security. This process of price discovery is one of the primary purposes of a market. However this framework of a single central market is not relevant as trading has dispersed over several venues and the theoretical central market is, in reality, fragmented. Whereas earlier, the traded price in the single central market could be considered a good proxy for the efficient price, with fragmented information flow that is no longer the case. The efficient price is no longer observable and the processes of price 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 has a significant impact on the price discovery process.

II. Literature Review

The issue of fragmented markets was first addressed by Garbade and Silber (1979). They examine the short-run behavior of the prices of same or identical assets traded on the NYSE and regional exchanges. They introduce the dominant-satellite idea of one market providing the bulk of new information while the others follow i.e. have a minor contribution or none at all. Garbade, Pomerenze and Silber (1979) empirically examine the information content of prices in dealer markets and find that the average price does not contain all the information. Glosten and Harris (1988) proposed a model in which the efficient price innovations arise from trade size and direction. Madhavan, Richardson and Roomans (1997) model the direction of trades as an autoregressive process. It models a more persistent dependency than the MA specification of structural models. Stoll and Whaley (1990) investigate 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. Their methodology consists regressing the leads and lags of one set of returns on the other. Though the lead-lag treatment may be used to make broad general statements about precedence in time, from an econometric perspective the models are misspecified. The models assume convergence of parameters where it can be demonstrated that the aggregation of error process do not converge. The treatment in all these papers does not use the co-integration concept explicitly. The richer covariance structures of co-integration analysis shed greater light on the dynamics of price behavior.

The arguments concerning reduction of tick-size center around on one hand, that smaller increments would increase competition, fall in spreads and better price improvement. The other side claims that it would make front running easier, depth decreases and dealers will not display order size and change to market order strategy. This would make markets less transparent. Harris (1991) shows that liquidity providers in both exchange and dealer markets prefer a small set of discrete prices to reduce negotiation costs. 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 (1996) find that spreads decline but volume did not go up much. Porter and Weaver (1997) report results similar to Harris (1994) from their study the effect of changing tick size at the Toronto Stock Exchange. Besides this, there is some evidence that prices are less sticky with smaller tick-size.

Harris (1997) reviews arguments for and against decimalization. One view that emerges is that the tick-size effect may vary by the amount of information that an exchange publishes. Bessembinder (1997) 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 what new information dictates.

Bacidore (2001) explicitly addresses the informational impact of decimalization. Reduction in transaction costs with smaller tick-size has been well documented. Bacidore (1997) and Bessembinder (1997) show that a part of the fall in the spread is due to reduction in the adverse selection component. Bacidore shows that traders are more willing to become informed as tick-size increases. There is a counter argument that wider spreads are more likely to straddle the true price and therefore there is less incentive to obtain information. There are several strands of literature on the informational effects of decimalization. One states that decimalization decreases transparency and information. Harris (1991) had shown that limit orders would 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. Price changes will occur at minimum tick-size, rather than as new information dictates. Moreover 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 improvement faster and prices will be less sticky.

Narrower spreads make it more likely that the efficient price is not within the spread and consequently there is inducement to uncover more information. Therefore if decimalization had in fact improved incorporation of new information and prices are less sticky we should see faster 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. That is if a tick of 12.5 cents is in force and one venue increases its prices by this amount the other venues wish to adjust their prices they must do so in multiples of this tick. There is no choice for them to compete by revising their prices gradually by small amounts. They are forced to make a change of 12.5 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 as would have been necessary in the earlier case. This would mean that the prices will take a much longer time to converge. This in turn will prolong the effect of any shock i.e. the markets would take longer to reach equilibrium. 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.

H1: The Impulse Responses of the permanent components would take significantly longer periods to converge after decimalization.

H2: The information share of markets will not be significantly affected by decimalization

III. Data and Methodology

Decimalization of stock prices was implemented in phases starting in August 2000. The SEC mandated that all exchanges must complete the implementation by April 2001. This paper follows Hasbrouck (1995).Three months of Bid and Ask 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 is a three month window from May to August of 2000. The post implementation period extends from May to August of 2001.

Following Hasbrouck (1995), the Bid and Ask series are estimated separately instead of the mid-points as a single series. 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 prices at one second intervals from 9:30 AM to 3:45 PM. The high sampling rate is necessary for eliminating contemporaneous correlation.

The previous literature is concerned exclusively with information shares. This study examines the changes in information share levels. The purpose is to examine whether decimalization has changed the information shares and also the time taken for the prices of different markets to reach a new equilibrium *Estimation*

This study estimates a VMA model since the Impulse Response Functions are more readily obtainable from the VMA representation. The price series used for the Information Share 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

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

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 γ is the vector of speed of adjustment. The cointegrating vectors are in z_t. That is

$$z_t = \begin{bmatrix} p_{1t} - p_{2t} \\ p_{1t} - p_{3t} \end{bmatrix} = Fp_t \text{ where } F = [i - I_2] \text{ and } i \text{ is a vector of ones.} \qquad (2)$$

The VMA representation of the model is:

$$\Delta p_t = B_0 u_t + B_1 u_{t-1} + B_2 u_{t-2} ....where\ B_0 = I\ . \qquad (3)$$

If we assume that $\Delta p_t = 0$ and $z_t = u_t$ at times t = -1, -2, -3 ...., now if at time t = 0 there is a unit shock u_0 =[1 0 0]' then since $\Delta p_t = 0$ at t = 0, we have $\Delta p_0 = [1\ 0\ 0]'$ and

$$\left.\begin{aligned} z_0 &= \mu_z + F\Delta p_0 \\ \Delta p_1 &= A_1\Delta p_0 + \gamma z_0 \\ z_1 &= z_0 + F\Delta p_1 \\ \Delta p_2 &= A_1\Delta p_1 + A_2\Delta p_0 + \gamma z_1 \end{aligned}\right\} \qquad (4)$$

In the VMA representation the first column of B_0 is Δp_0 and the first column of B_1 is Δp_1 etc. To obtain the second columns of B_0, B_1 etc the system is forecasted for shocks u_0 =[1 0 0]' and u_1 =[0 1 0]' etc.

$$C_k = \sum_{i=0}^{k} B_k \text{ (cumulative impulse response functions. Look at appendix)} \qquad (5)$$

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 $\sigma_w^2 = c\ \Omega\ c'$

the information share of the i^{th} market $IS_i = \dfrac{c_i^2 \sigma_i^2}{\sigma_w^2}$, (6)

If the covariance matrix Ω is not diagonal then all the orderings of the Cholesky decompositions must be computed. In this study we have three orderings. 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. The information share of each market as a percentage of the total information inflow for each of the securities is estimated for the pre and post event samples. However as the Cholesky decomposition will produce a maximum and minimum estimate the midpoint is taken as the information share. These pre and post midpoints are used to conduct a test of proportions to determine any increase or decrease of information shares of the markets.

The impulse responses are obtained from the VMA representation, by imparting a unit shock to each of the markets and observing the time taken for equilibrium to be reached. The difference in the time taken before and after the implementation of decimalization is tested for significant changes.

IV. Empirical Results

The price series were first tested to ascertain that they contained a unit root with the Augmented Dickey-Fuller (ADF) Test. Next the series were tested for Granger causality to establishes whether past innovations in one series affect the current values of another series. The Johansen Trace and Maximum Eigen Value tests were used to verify that the price series are cointegrated and that at least two cointegrating vectors exist. The tables for these tests are omitted due to space considerations.

A. Information Share and Impulse Response Estimates

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

The estimates of the maximum and the minimum IS information share for the 2000 Bid and Offer series and the standard errors are contained in Table I and II. The results show the estimates of the information share for each of the twenty five stocks at Boston, Cincinnati and the NYSE. The standard errors show that the estimates are highly significant. Not surprisingly, NYSE contributes the bulk of the new information i.e. from 80-95%, next to NYSE Cincinnati contributes 10 – 15% and Boston about 2-5%. It must be noted that these measures are relative and do not actually measure the exact amount of information in the market. The measure simply decomposes the variance of the efficient price and attributes a percentage of it to each market. If more markets are included then the shares will change. This study is trying to establish changes to shares rather than absolute information shares. Tables III and IV contain the information shares for the 2001 Bid and Offer series. Once again we see a similar distribution of information shares between the three markets. The mid points of these estimates will be used in tests for changes.

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 causal nature of cointegration. 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 constituent the series converge.

In the present model the variables are quote series from Boston, Cincinnati 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. Figures 1 and 2 are representative samples of the 300 such impulse response graphs. The top left panel of Figure 1 shows the effect of a unit impulse to Boston 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 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. That is the new equilibrium of 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 NYSE quotes. The 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 NYSE which contributes more than 90% of new information. The other figures are further examples of the impulse response functions.

The Impulse Response Functions are tabulated in Tables V - XVI. These tables report how long the prices in each market were adjusting before the system reached a new equilibrium. Note that these are innovations to that efficient price and as such have a permanent effect on the long run equilibrium price. Tables V, VI and VII show the estimates of the impulse responses after a unit shock is delivered to Bid series of Boston, Cincinnati and NYSE from 2000, while Tables VIII – X show the impulse responses to the Bid series from 2001. The impulse responses to the Offer series from 2000 and 2001 are shown in Tables XI – XVI. 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. However it must be recalled that for the sake of estimation level of convergence is measured to three decimal places (equivalent to millisecond precision). In real markets convergence occurs at the minimum tick i.e. if the tick is 10 cents then all changes take place at steps of 10 cents. In this econometric analysis we are by construction making it possible to move in very small steps. The results show that the impulses to Boston and Cincinnati do not retain much of their impact on the efficient price i.e. the shock goes down after some time to a small fraction. However an impulse the NYSE series retains most of its effect. This is to be expected since NYSE is the dominant market where you expect informed traders to participate. Hence any innovations in this market have a large impact on the efficient price.

Formal t-tests for changes of the time taken for prices to converge to a new equilibrium of each venue are reported in Tables XVIII and XIX for the Bid and Offer series. As can be seen clearly the time taken for the system to stabilize i.e. for the changes in each venue to converge is much longer after decimalization, proving hypothesis H1. The difference is significant at less than the 1% level. Recall that these are the long run impact on an innovation on the prices at each market; these are obtained from the rows of the C(1) matrix which are all identical.

The results of changes of information shares of each market are reported in Tables XX and XI for the Bid and Offer series. As predicted by hypothesis H2, decimalization has not changed the information shares of the markets significantly. The difference in means of the information shares is not significant at any level.

V. Summary and Conclusions

The study has shown that decimalization has not significantly improved informational parity of markets. However it seems to have significantly increased the time taken for markets to stabilize after an informational shock. At an earlier time the minor effect of the markets taking a longer time to reach equilibrium would have little consequence as the trading process was slow. But with the advent of high frequency trading where the time resolutions are in micro seconds even a few fractions of a second could deliver significant advantage to institutional traders and individuals who have direct market access (DMA) and use algorithmic trading and trade in volumes large enough to overcome transaction costs. This can result in the unintended consequence of giving them an unfair advantage. It is therefore absolutely necessary to proceed cautiously before any changes to the microstructure of markets are implemented. However the results of this study are by no means an argument against change. The cointegration estimation procedure of measuring the information is very sensitivity of to noise and contemporaneous correlation. Therefore the results must be viewed as indicators and not as absolute proof. Further research should be conducted using price series from other market venues.

Table I: Upper and Lower bounds of Information Shares 2000 Bid Series

	Information Share(IS) Maximum Estimates: Series 2000 Bid						Information Share(IS) Minimum Estimates: Series 2000 Bid					
Stock	Boston		Cincinnati		NYSE		Boston		Cincinnati		NYSE	
	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 II: Upper and Lower bounds of Information Shares 2000 Offer Series

	Information Share(IS) Maximum Estimates: Series 2000 Ofr						Information Share(IS) Minimum Estimates: Series 2000 Ofr					
Stock	Boston		Cincinnati		NYSE		Boston		Cincinnati		NYSE	
	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 III: Upper and Lower bounds of Information Shares 2001 Bid Series

	Information Share(IS) Maximum Estimates: Series 2001 Bid						Information Share(IS) Minimum Estimates: Series 2001 Bid					
Stock	Boston		Cincinnati		NYSE		Boston		Cincinnati		NYSE	
	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 IV: Upper and Lower bounds of Information Shares 2001 Offer Series

	Information Share(IS) Maximum Estimates: Series 2001 Ofr						Information Share(IS) Minimum Estimates: Series 2001 Ofr					
Stock	Boston		Cincinnati		NYSE		Boston		Cincinnati		NYSE	
	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 V: Impulse Responses 2000 Bid Series
Unit Impulse to Boston

Impulse Responses: Series: 2000 Bid				
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 VI: Impulse Responses 2000 Bid Series
Unit Impulse to Cincinnati

Impulse Responses: Series: 2000 Bid				
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 VII: Impulse Responses 2000 Bid Series
Unit Impulse to NYSE

Impulse Responses: Series: 2000 Bid				
Unit Impulse to NYSE				
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 VIII: Impulse Responses 2001 Bid Series
Unit Impulse to Boston

Impulse Responses: Series: 2001 Bid				
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 IX: Impulse Responses 2001 Bid Series
Unit Impulse to Cincinnati

Impulse Responses: Series: 2001 Bid				
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 X: Impulse Responses 2001 Bid Series
Unit Impulse to NYSE

Impulse Responses: Series: 2001 Bid				
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 XI: Impulse Responses 2000 Offer Series
Unit Impulse to Boston

Impulse Responses: Series: 2000 Ofr				
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 XII: Impulse Responses 2000 Offer Series
Unit Impulse to Cincinnati

Impulse Responses: Series: 2000 Ofr				
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 XIII: Impulse Responses 2000 Offer Series
Unit Impulse to NYSE

Impulse Responses: Series: 2000 Ofr				
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 XIV Impulse Responses 2001 Offer Series
Unit Impulse to Boston

Impulse Responses: Series: 2001 Ofr				
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 XV: Impulse Responses 2001 Offer Series
Unit Impulse to Cincinnati

Impulse Responses: Series: 2001 Ofr				
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 XVI: Impulse Responses 2001 Offer Series
Unit Impulse to NYSE

Impulse Responses: Series: 2001 Ofr				
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 XVII: Difference in Mean Convergence Time Bid Series

Impulse Responses Tests: Decimalization: 2000-2001 Series 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 XVIII: Difference in Mean Convergence Time Offer Series Series

Impulse Responses Tests: Decimalization: 2000-2001 Series Ofr					
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 XIX: Difference in Mean Information Share level Bid Series

Information Share Tests: Decimalization: 2000-2001 Bid Series					
Exchange	Mean		Difference	P-Value	Variance
	Pre	Post	Post - Pre		P-Value
Boston	0.1089	0.1236	0.01470	0.3702	0.3306
Cincinnati	0.0640	0.0604	-0.00352	0.5124	0.6801
NYSE	0.7385	0.7342	-0.00430	0.8866	0.4416

Table XX Difference in Mean Information Share level Offer Series

Information Share Tests: Decimalization: 2000-2001 Ofr Series					
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

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Figure 1: Impulse Responses 2000

Impulse Response Functions: Series 2000

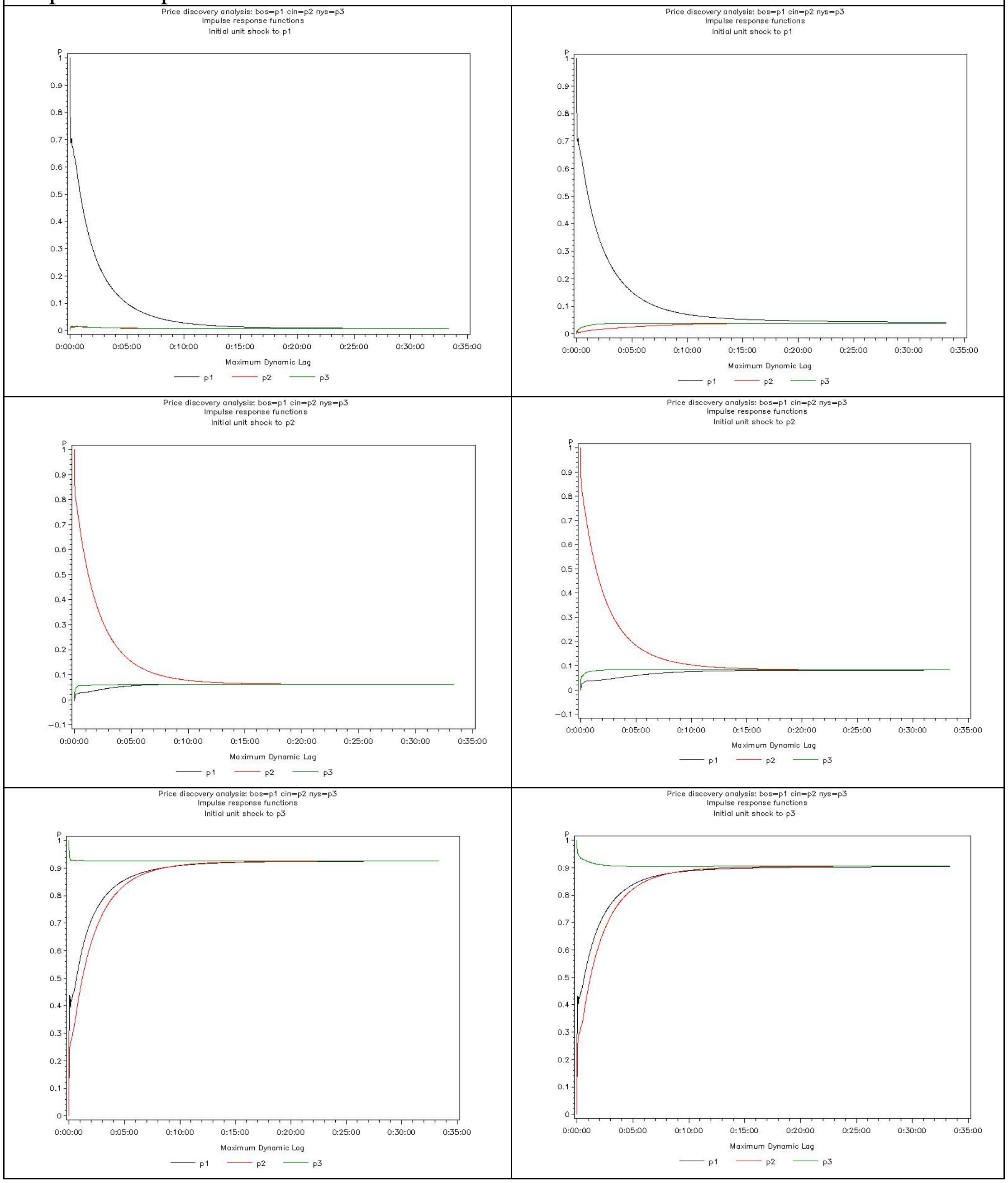
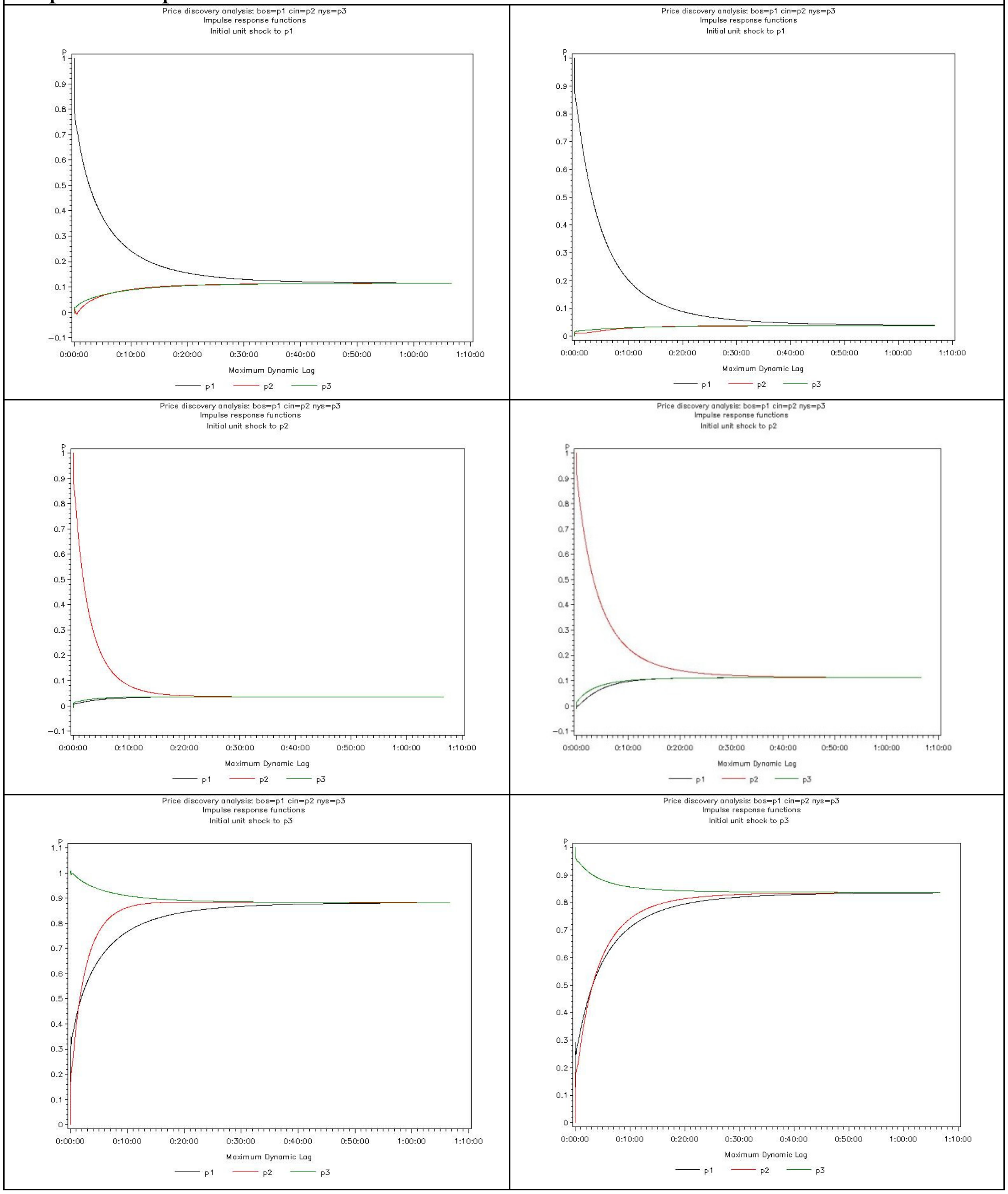


Figure 2: : Impulse Responses 2001

Impulse Response Functions: Series 2001



APPENDIX

Review of Cointegration

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

The time-series of a random variable $\{X_t\} = \left(x_{1,} x_{2,} x_{3}, \ldots x_t\right)'$ is considered weakly or covariance stationary if it has a constant mean, finite variance and the covariance is a function of the "distance" between different observations. A set of non-stationary variables is said to be cointegrated when some linear combination(s) of them is stationary. If we have $\{X_t\} = (x_{1t}, x_{2t}, x_{3t}, \ldots x_{kt})$ i.e. a vector of *k* non-stationary variables each of which is integrated of order d i.e. I(d). They are cointegrated if some linear combination(s) of them is integrated of order I(d-b) where b≤ 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 I(0) i.e. stationary.

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

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

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

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

Since e_t is stationary $\beta' X_t$ is also stationary and β is a cointegrating vector (CI). However since β is a linear combination then any scalar multiple λβ is also a cointegrating vector for λ≠0. Consequently, the cointegrating vector is not unique. The cointegrating vector is usually normalized by one of the parameters $\beta' = \left(1, -\frac{\beta_1}{\beta_0}, -\frac{\beta_2}{\beta_0}, \ldots\ldots -\frac{\beta_n}{\beta_0}\right)$ i.e. normalized by β_0. The long-run equilibrium relationship is represented by $Y_t - (\beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \ldots\ldots \beta_k x_{kt}) = 0$ 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 ≤ (k-1). In the above analysis where β was deemed to be a vector, we are implicitly assuming a unique cointegrating vector. But there could be several CIs and β is usually a (k x r) matrix of rank r, whose columns are cointegrating vectors.

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

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

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

$\Delta X_t = \Gamma X_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta X_{t-1} + e_t$ where $\Gamma_i = (k \text{ x } k)$ 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(α) = rk(β) = some r < k, rk(Γ)= r.

Since $\Delta X_t, \sum_{i=1}^{p} \Gamma_i \Delta X_{t-1}$ and e_t are all stationary ΓX_{t-1} which is the only expression that includes I(1) variables, must also be stationary. Therefore ΓX_{t-1} contains the cointegration relations

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

Let $X_t = (X_{1t}, X_{2t}, ...X_{kt})'$ be a vector of *k,* I(1) variables with t = 1,2, ….T. If X_t is a first order Vector Auto Regressive process then $X_t = X_{t-1} + e_t$ where e_t is a white noise vector i.e. $e_t = (\varepsilon_{1t,}\varepsilon_{2t,}......\varepsilon_{kt,})'$, then $\Delta X_t = e_t$ By the Wold Decomposition Theorem ΔX_t has an infinite Vector Moving Average (VMA) representation $X_t = C(L)e_t$ that is $\Delta X_t = c_0 e_t + c_1 e_{t-1} + c_2 e_{t-2} ......\infty = C(L)e_t$ where $C(L) = c_0 + c_1 L + c_2 L^2 + c_3 L^3 ...\infty$ and L is the lag operator and c_j is a (*k* x *k*) diagonal coefficient matrix. The matrix polynomial C(L) can be written as $C(L) = C(1) + (1\text{-}L)C^*(L)$

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 $(1\text{-}L)C^*(L)$ 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

$$X_t = X_0 + C(1)\sum_{i=1}^{t} e_i + (1-L)C^*(L)e_t$$

The term $C(1)\sum_{i=1}^{t} e_i$ will contain the non stationary elements i.e. the stochastic trends which cause permanent effects on X_t and $(1-L)C^*(L)e_t$ will contain the transient effects. It is this permanent component which is analyzed to obtain the information shares.

The Vector Moving Average form is $X_t = X_0 + \Gamma \sum_{i=1}^{t} e_i + \Gamma^*(L)e_t$.

Johansen (1991) shows $\Gamma = \beta_\perp \left[\alpha_\perp \left(I_k - \sum_{i=1}^{p-1} \Gamma_i \right) \beta_\perp \right]^{-1} \alpha_\perp'$ and $\Gamma^*(L)e_t = \sum_{j=0}^{\infty} \Gamma_j^* e_{t-j}$

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

Demand Elasticity Estimates for Major League Baseball: Atlanta Braves

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Abstract

A structural model capturing franchise-level pricing behavior of member teams within Major League Baseball is specified and empirically evaluated to determine how selected factors influence demand for in-person attendance at Major League Baseball games. In-person attendance is purported to subscribe to the basic law of demand with number of tickets demanded inversely related to the own price of seats, directly related to the expected level of the team's performance and adversely influenced by price and availability of substitute forms of entertainment services available within the market area. The elasticity of demand for the team's home games is estimated at -1.281 suggesting that this particular major league team set its price at the profit-maximizing level.

JEL L83: Industrial Organization

I. Introduction

Rapidly rising ticket prices have made professional sports an increasingly fruitful area of economic research. Demand analyses have been conducted on Major League Baseball [Demmert (1973), Hill, Madura and Zuber, (1982), Hunt and Lewis, (1976), Whitney (1988), Kahane and Shmanske (1997), Bird (1982), Scully (1989), Zimbalist (1992), Cofin (1996), Fort and Quirk (1996), Hadley and Poitras (2002), Winfree, McCluskey, Mittelhammer and Fort (2003)]; minor league baseball [Seigfried and Eisenberg, (1980)]; football Seigfried and Hinshaw (1979)]; soccer [Bird, (1982); Jennett, (1984)]; ice hockey [Jones, (1984)]; and cricket [Shofield, (1983)]. Consequences of the organizational structure of the sports industry on admission prices, salaries of participating athletes, labor market discrimination, revenue sharing from gate receipts and media advertising, and uncertainty of outcome of games on fan interest are just a few areas that have attracted a vast amount of literature Scully (1972), Noll (1974), Whitney (1988), and Knowles et al. (1992). Others have investigated the economic ramifications of such issues as the reserve clause, free agency, the rookie draft, payroll caps, competitive balance, player mobility, and salaries Daly and Moore (1981), Scully (1989), Fort and Quirk (1995),Vrooman (1995, 1996); Depken (1999) and Eckard (2001).

In spite of the frequent criticism leveled at owners of major league professional baseball teams for charging too much for admission to their games, the research literature suggests that on the contrary team owners are charging prices less than those that maximize profit. In fact, the research literature suggests that ticket prices are routinely set in the inelastic range of owners' demand curves. If indeed team owners set prices below their profit maximizing level, we are left with the difficult task of explaining what team owners seek to achieve.

A major concern with previous demand studies is that ticket prices and attendance are considered exogenously determined. Treating price and quantity of seats demanded as exogenously determined produces results that are inconsistent with those which economic theory would predict. Noll (1974), Scully (1989), Coffin (1996), and Irani (1997), for instance, suggest that owners of major league baseball teams tend to set admission prices in the inelastic range of demand. On the contrary, standard economic theory purports that members of a professional sport league consisting of profit-maximizing monopolists in their respective geographical markets would set ticket prices in the elastic range of their demand curves

II. Purpose and Approach

This paper seeks to resolve this inconsistency between what economic theory predicts and findings in the literature by conducting a careful study of the influence of price on attendance and supply of seats at professional baseball games. Its primary objective is to estimate an attendance demand equation for one Major League Baseball team. Attendance demand is postulated as positively related to the general level of income of the relevant population inversely related to the price of admission to baseball games in relation to the prices of goods in general including recreational substitutes (Hill, Madura and Zuber, 1982). Attendance at baseball games is purportedly a positively related to the size of the population of the geographic area that comprises the territory in which the team has the exclusive right to play (Kahane and Shmanske, 1997). Attendance also depends on the size and convenience of access to the ballpark; the average rank or standing of the team during the season in the competition of its league; labor market strikes; roster turnover; competitive balance; new stadiums. Attendance is a negatively related to availability of leisure time alternatives to baseball games in the area as well as percentages of games won by teams in the league. More specifically, in-person attendance subscribes to the basic law of demand in that number of tickets demanded is inversely related to the own price of seats, directly related to the expected level of the team's performance against its opponent and adversely influenced by price and availability of substitute forms of entertainment services within the market area.

This study follows the traditional literature on spectator sports but also provides rare support for the robust predictions from economic theory. On the other hand, the study departs from the existing literature by focusing less broadly in comparison to prior studies. More specifically, it evaluates ticket-pricing behavior for one franchise within major league baseball in hope of relying on a consistent data set over a 37-year period. A structural model characterizing franchise-level pricing behavior of a member team within Major League Baseball is specified, and the influence of selected factors on demand for in-person attendance at professional baseball games empirically evaluated.

Unlike much of the existing literature, this study not only take into account that both ticket price and attendance are determined endogenously through the interaction of exogenous demand and supply factors, but win-loss percentage is also treated exogenously. Two-Stage-Least Squares (TSLS) are used to estimate supply and demand functions. Limited information maximum likelihood is used to quantify the influence of ticket prices and wages of professional players on demand for in-person attendance at baseball games.

III. Empirical Model

Demand for major league baseball depends only on the price of a seat at the game and the team's performance during the prior season of play. In-person attendance at major league baseball games is postulated as inversely dependent on the real price of admission tickets and a positive function of the expected performance during the prior season (Whitney, 1988). The supply relationship assumes that the supply of seats is a positive function of the price of seats, a negative function of the salaries of player inputs, and a trend term to capture secular shifts in the supply function. The behavioral model representing demand, supply, and win percentage takes the following linear functional form:

$$Q^{D}{}_{t} = \alpha_0 + \alpha_1 P_t + \alpha_2 WL^{*}{}_{T-1} + \mu_{1T} \tag{1}$$

$$P_T = \beta_1 + \beta_2 Q^{S}{}_{T} + \beta_3 S_T + \beta_4 TRND + \mu_2 \tag{2}$$

$$Q_T^D = Q_T^S = Q_T \tag{3}$$

For purposes of the empirical investigation **Q_T** is an index for total attendance per season with 1982-1984=100. **P_T** is a weighted average price of seats at the ballpark with number of seats available within the various sections serving as weights. The average ticket price is converted to and index again with 1982-84=100 and the index is deflated by the Consumer Price Index for the metropolitan area. **WL_{t-1}** is the team's win-loss record for the previous season of play. More specifically, it is the percentage of the home games played that the team won during the prior season. It is used in this paper as a measure of fans' anticipation regarding the quality of the games to be played during the current season.. **S_t** is the average salary paid to Major League Baseball players nationally and therefore is considered a major cost factor in ticket pricing decisions. This is a supply factor that is expected to force the team owners to raise the supply price of seats overtime as salaries of players rise. **TRND** is a trend variable designed to incorporate the effects of factors not explicitly included in the model that are likely to influence attendance. Its value begins with 1969=0 and ends with 2004=37.
Assuming equilibrium in the market for baseball tickets (equations 1-2) enables us to solve equations (1) and equation (2) simultaneously for equilibrium price and quantity. The structural model gives rise to the following matrix representation of two reduced-form equations to estimate the two instruments included in our model:

$$\begin{bmatrix} Q_T \\ P_T \end{bmatrix} = \begin{bmatrix} \frac{-(\beta_2\alpha_1 - \alpha_2\beta_1)}{(-\beta_2+\alpha_2)} & \frac{\beta_2}{(\beta_2-\alpha_2)}\alpha_3 & \frac{-\alpha_2}{(\beta_2-\alpha_2)}\beta_3 & \frac{\beta_4}{(-\beta_2+\alpha_2)}\alpha_2 \\ \frac{-(\alpha_1-\beta_1)}{(-\beta_2+\alpha_2)} & \frac{1}{(\beta_2-\alpha_2)}\alpha_3 & \frac{-1}{(\beta_2-\alpha_2)}\beta_3 & \frac{\beta_4}{(-\beta_2+\alpha_2)} \end{bmatrix} * \begin{bmatrix} 1 \\ WL_{T-1} \\ S_T \\ TRND \end{bmatrix} \qquad (4)$$

Only one endogenous variable appears on the right-hand side of the supply equation (2), **Q^S,** and only one of the four exogenous variables, **WL_{T-1}**, is excluded from the supply equation. The structural parameters in the supply equation can therefore be determined by applying the standard OLS to evaluate the reduced-form equations. We are able to calculate unambiguous parameters for the supply equation. That is, the application of Ordinary Least Squares to estimate the reduced form equations provides adequate information to provide consistent estimates of the structural coefficients in the supply equation. The following vector describes how the structural coefficients in the supply equation are derived from estimating the reduced-form equations:

$$\begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{bmatrix} = \frac{1}{\pi_{22}} \begin{bmatrix} -(-\pi_{11}\pi_{22} + \pi_{21}\pi_{12} \\ \pi_{12} \\ (-\pi_{23}\pi_{12} + \pi_{13}\pi_{22}) \\ (-\pi_{24}\pi_{12} + \pi_{14}\pi_{22} \end{bmatrix}$$

π_{ij} represents the ith and jth element of the 2x5 matrix on the right hand side of equation (4).

IV. DATA

The Atlanta Braves, a member of the National League East Division of Major League Baseball, was selected for empirical investigation of hypotheses advanced in this paper. Using the Atlanta Braves offers an excellent opportunity to evaluate the influence of uncertainty of outcome on demand for professional sports. In each of the fourteen years since 1991, the team has been successful at winning the National League East division title. Attendance initially rose with the team's success but has since declined. Could this declining pattern provide supporting evidence of uncertainty of outcome at work? In light of its recent history of the team not being able to win the World Series, do fans place less value on the team's success at winning individual games? In other words, is uncertainty of outcome working against the Atlanta Braves organization? Time series data with respect to seat prices at home games, number of seats offered by seat-quality category, seasonal attendance, and the franchise's win-loss performance record were assembled for the period from 1966 to 2004 from a variety of published sources. This data is presented in Table 1.

[Table 1 Here]

Ideally, such a study as this one calls for **ticket price**s that represent the value that fans are willing to pay for a particular seat category and not the supply price of those particular seats as offered by the Atlanta Braves franchise. Absence team gate revenue data, however, neither the price that fans pay nor what they are willing to pay are directly observable. Instead, what we have constructed a weighted average of seat prices charged by the organization each year with weights as proportions of seats that the franchise made available in the respective quality categories. Such a price measure implicitly assumes fans attending baseball games are seated at the ballpark in proportion that seats are physically made available. While this is not strictly true, there is no reason to believe that use of such an assumption introduces any systematic bias in the ticket prices. To control for the changes in prices of goods and services other than ticket prices on demand for seats during the sample period, the seat prices were deflated using the CPI for the Atlanta Metropolitan Area. Thus, ticket prices used in this article are the inflation-adjusted average ticket prices measured in comparison to the cost of a typical basket of goods and services in the metropolitan area where home games are played.

Winning percentage for the Atlanta Braves also is a crucial variable to the attendance demand model. The expected sign of the coefficient on this variable is positive for two reasons. First, not only do fans enjoy seeing the home team play, a win enhances that level of enjoyment. Second, fans like to see the team win or at least contend for the championship. Both of these effects are captured by this variable. Other studies have used alternative constructions of this variable, such as number of games out of the first-place position at various points in the season. Most measures are significant indications of fans' perceptions of the team's probability of winning and therefore produce similar outcomes. We chose percent of games won out of the total number of games played during the season partly because of ease of access of this measure of ticket price.

Salaries paid to Major League Baseball players is also an inflation-adjusted index of the average of what all 26 league members pay for player talent and is not specific to the Atlanta Braves. Player salary data from the Associated Press (AP) is only available since 1988. We therefore obtained annual player salary data from 1969 to 2004 from Major League Baseball. Per capita income, Consumer Price Index, and the population of metropolitan Atlanta, Georgia were obtained from secondary sources of the Bureau of the Census. To facilitate interpretation of the results, data on actual values for these variables were transformed into indexes with 1982-1984=100 to render all data series consistent with the consumer price index. The data series runs from 1966, the beginning of the Atlanta Braves franchise, through 2004, the latest year for which data was available.

V. Empirical Results

The empirical results using OLS to estimate the reduced-form equations are as follows including the respective t-statistics:

$$Q_T = -82.09 + 2.454WL_T + 0.172SAL_T + 1.307TRND \qquad R^2 = 0.845 \quad \textbf{(6)}$$
(2.80) (4.38) (1.61) (1.041)

$$P_T = 105.2 + 0.804WL_T + 0.647SAL_T - 6.115TRND \qquad R^2 = 0.945 \quad \textbf{(7)}$$
(2.74) (1.10) (4.556) (3.451)

The estimated reduced-form model explains approximately four-fifths of the annual movement in Atlanta Braves attendance and ninety-five percent of movements in the team's ticket prices over the period from 1966 to 2004. The signs of the coefficients of variables included in both the quantity and price equations are consistent with expectations. While win-loss percentage is positive and significantly related to attendance it is not significantly related to the supply price of ticket. On the other hand, salary of baseball players had a positive and statistically significant effect on the supply price of tickets but had no significant effect on the number of persons willing to purchase tickets. The estimates show no significant trend in demand for seats but a significant decline in the real supply price of seats.

The empirical estimates for the reduced-form equations permit us to estimate the structural supply function for baseball tickets (numbers in parentheses represent t-statistics for the corresponding coefficients):

$$\mathbf{Q^S} = -403.187 + 3.052\, \mathbf{P_T} - 1.802\, \mathbf{SAL_T} - 0.043\, \mathbf{TRND} \qquad \textbf{(8)}$$
(6.297) (7.016) (5.395) (6.204)

The empirical results for the supply equation are impressive and are consistent with theoretical expectations. According to these findings, the inflation-adjusted price the team charges for its tickets is positively related to the quantity of tickets it is willing to supply, as economic theory predicts. A one percentage point increase in the real price of baseball tickets adds approximately 3 percentage points to the index of the number of seats the team is willing to offer. Salary of players also contains the expected negative impact on the number of seats that the organization is willingness to supply at any given price as theory purports. A one percentage point increase in the index of real salaries of professional baseball players reduces the index of the number of seats the team is willing to supply by 1.8 percentage points. Finally, a secular decrease in the number of seats that the organization is willing to supply is evident from the trend term. Other things equal, the team is willing to supply approximately 4.3 percent fewer seats per year. All variables are significant at at-least the one percent level.

The demand function is over-identified. Only one right-hand endogenous variable appears in the demand equation, while two of the four exogenous variables in the system are excluded. In short, the use of the reduced-form equations provides for more than one value for α_2, the coefficient in the demand equation. To estimate the over-identified demand equation in our empirical model, we turned to a Limited-Information-Maximization-Likelihood approach known as Least Variance Ratio principle (Kmenta, 1986, Johnson, 1984). This procedure permits us to estimate the parameters for a single equation within a system of equation without estimating other equations in the entire system.

The LVR procedure provides for the following estimated equation for the demand for baseball tickets. The Breusch-Pagan (B-P) test was used to evaluate the demand equation for heteroscedasticity (Breusch and Pagan, 1979). The results from performing the B-P test using win-loss record, salaries of athletes, and a time trend as predictors of the error term produced

$\chi^2(p=3)$ =2.78, lower than the critical value, $\chi_c^{\ 2}$ = 7.83. Thus, the results indicate absence of heteroskedasticity at the one percent level of significance.

$$\mathbf{Q^D} = -146.429 - .823\, \mathbf{P_T} + 6.905\, \mathbf{WL_{T-1}} \qquad \mathbf{R^2 = 0.495} \qquad \mathbf{F = 22.3} \qquad \mathbf{(9)}$$
$$(6.28) \quad (5.755) \quad (11.566)$$

Both ticket price and percentage of games won variables are statistically significant, contain their expected signs, and are consistent with economic theory. Ticket price has its expected negative effect on the quantity of seats demanded. A percentage point increase in the index for real price of Atlanta Braves baseball tickets reduces the index of tickets demanded by **1.258** percentage points (using mean real price index and index of attendance). This finding is consistent with the proposition that the team is a profit- maximizing firm with some degree of market power. The estimated coefficient is also significantly different from unity suggesting that the Atlanta Braves price their tickets to home games in the elastic range of the demand curve.

Prior-year performance of the team in on-the-field play also has a positive influence on the willingness of fans to purchase tickets to games in the approaching season. A one percentage point increase in percent of games won during the prior playing season increased the attendance in the following season by almost seven percentage points.

The results of the empirical estimates for the attendance model are shown in Figure 1. The Figure shows the actual index of attendance along with that which is predicted by the model. Given the limited number of variables used to estimate the model, we consider the results to e somewhat impressive.

[Place Figure 1 Here]

VI. Conclusions

Our empirical findings obtained from subjecting the model to Atlanta Braves data for the years from 1966 to 2004 are in agreement with expected results. Additionally, the findings are in agreement with those which standard economic theory would purport. More specifically, the quantity of seats demanded is inversely related to the own price of tickets to home games and the long-run elasticity is in excess of unity suggesting that the team owner of the Atlanta Braves set prices to maximize profits. Consistent with findings elsewhere, the team's prior-year performance on the field had a highly significant and positive influence on the subsequent year's attendance. The supply of seats also conforms to that which economic theory predicts. The number of seats offered by the team directly relates to the supply price of seats. Rising salaries of professional athletes were partly responsible for the rising supply price of seats. Finally, a secular increase in the supply price of seats to home games is determined.

Our empirical evaluation for the demand and supply for professional baseball allows us to also draw other interesting conclusions regarding professional baseball. First, our findings indicate that the Atlanta Braves organization set ticket prices in the elastic portion of its demand. Our results are contrary to those of others but are quite consistent to what theory would predict for a territorial monopolist. Indeed, demand elasticity is greater than unity and supply elasticity is well above unity consistent with low enterprises with negligible incremental cost of attendance. Long-run own-price demand elasticity for home games of the Atlanta Braves baseball franchise is estimated at **-1.258** (evaluated at the mean)**,** well within the elastic range of the demand curve and consistent with the hypothesis that the teams behavior depicts that predicted by a profit maximizing territorial monopolist**.** Supply elasticity, on the other hand, is determined to be **4.663,** also consistent with an enterprise with negligible marginal cost**.**

Appendix

Least Variance Ratio (LVR) is used to derive the parameters for estimating the demand equation (9) required to evaluate the following matrix expression using the empirical data:

$$Y_{1\Delta} = \begin{bmatrix} Q_1 & P_1 \\ Q_2 & P_2 \\ . & . \\ . & . \\ Q_{34} & P_{34} \end{bmatrix} \quad X_1 = \begin{bmatrix} 1 & WL_1 \\ 1 & WL_2 \\ . & . \\ . & . \\ 1 & WL_{34} \end{bmatrix} \quad X = \begin{bmatrix} 1 & WL_1 & SAL_1 & TRND_1 \\ 1 & WL_2 & SAL_2 & TRND_2 \\ . & . & . & . \\ . & . & . & . \\ 1 & WL_{34} & SAL_{34} & TRND_{34} \end{bmatrix} \quad \beta_{1\Delta} = \begin{bmatrix} 1 \\ -\alpha_2 \end{bmatrix}$$

$$\gamma_1 = \begin{bmatrix} \alpha_1 \\ \alpha_3 \end{bmatrix}.$$

Where:

$Y_{1\Delta}$ = n x 2 matrix of observed values of the two endogenous variables: price and attendance;

X_1 = n x 2 matrix representing the intercept term in the demand equation and win-loss percent;

X = n x 4 matrix representing observed values for included exogenous variables in the system;

$\beta_{1\alpha}$ = 2 x 1 vector of price coefficient in the demand equation; and

γ_1 = 2 x 1 vector representing the intercept and win-loss variable in the demand equation.

To estimate the necessary parameters require that the following matrices be evaluated with the particular data pertaining to baseball;

$$W_{1\Delta} = \begin{bmatrix} \Sigma Q_T^2 & \Sigma Q_T P_T \\ \Sigma Q_T P_T & \Sigma P_T^2 \end{bmatrix} - \begin{bmatrix} \Sigma Q_T & \Sigma Q_T WL_T \\ \Sigma P_T & \Sigma P_T WL_T \end{bmatrix} \begin{bmatrix} T & \Sigma WL_T \\ \Sigma WL_T & \Sigma WL_T^2 \end{bmatrix}^{-1} \begin{bmatrix} \Sigma Q_T & \Sigma P_T \\ \Sigma Q_T WL_T & \Sigma P_T WL_T \end{bmatrix}$$

$$W_1 = \begin{bmatrix} \Sigma Q_T^2 & \Sigma Q_T P_T \\ \Sigma Q_T P_T & \Sigma P_T^2 \end{bmatrix} - \begin{bmatrix} \Sigma Q_T & \Sigma Q_T WL_T & \Sigma Q_T SAL & \Sigma Q_T TRND_T \\ \Sigma P_T & \Sigma P_T WL_T & \Sigma P_T SAL & \Sigma P_T TRND_T \end{bmatrix} \mathrm{X}$$

$$\begin{bmatrix} T & \Sigma WL_T & \Sigma SAL_T & \Sigma TRND_T \\ \Sigma WL_T & \Sigma WL_T^2 & \Sigma WL_T SAL_T & \Sigma WL_T TRND_T \\ \Sigma SAL & \Sigma SAL_T WL_T & \Sigma SAL_T^2 & \Sigma SAL_T TRND_T \\ \Sigma TRND_T & \Sigma TRND_T WL_T & \Sigma TRND_T SAL_T & \Sigma TRND_T^2 \end{bmatrix}^{-1} \begin{bmatrix} \Sigma Q_T & \Sigma P_T \\ \Sigma Q_T WL_T & \Sigma P_T WL_T \\ \Sigma Q_T SAL_T & \Sigma P_T SAL_T \\ \Sigma Q_T TRND_T & \Sigma P_T TRND_T \end{bmatrix}$$

Carrying out the procedure using data pertaining to the Atlanta Braves the above matrices become,

$$\mathbf{W}_{1\Delta} = \begin{bmatrix} 4.34*10^4 & 1.258*10^4 \\ 1.258*10^4 & 2.193*10^4 \end{bmatrix} \qquad \mathbf{W}_1 = \begin{bmatrix} 1.601*10^4 & -210.389 \\ -210.389 & 2.998*10^3 \end{bmatrix}$$

The determinant, ($\mathbf{W}_{1\Delta *}$-l$\mathbf{W}_1$), for these matrices amounts to the solution to a second-degree polynomial in l with the following roots:

$l_1 = 2.042$ and $l_2 = 8.103$

The procedure requires that we select the root whose value is closest to one. The solution becomes

$$[\mathbf{W}_1 - 2.042\ \mathbf{W}_1]\begin{bmatrix} 1 \\ -\alpha_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}.$$

The solution to the aforementioned two equations leads to the same value for $\ddot{\alpha}_2$. $\ddot{\alpha}_2$=-0.823

Substituting the empirical estimate for $\ddot{\alpha}_2$ enables us to derive the empirical values for γ_1:

$$\gamma_1 = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} T & \Sigma WL_T \\ \Sigma WL_T & \Sigma WL_T^2 \end{bmatrix}^{-1} \begin{bmatrix} \Sigma Q_T & \Sigma P_T \\ \Sigma Q_T WL_T & \Sigma P_T WL_T \end{bmatrix} \begin{bmatrix} 1 \\ 0.823 \end{bmatrix} = \begin{bmatrix} -146.429 \\ 6.905 \end{bmatrix}$$

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Figure 1. Predicted vs Actual Attendance

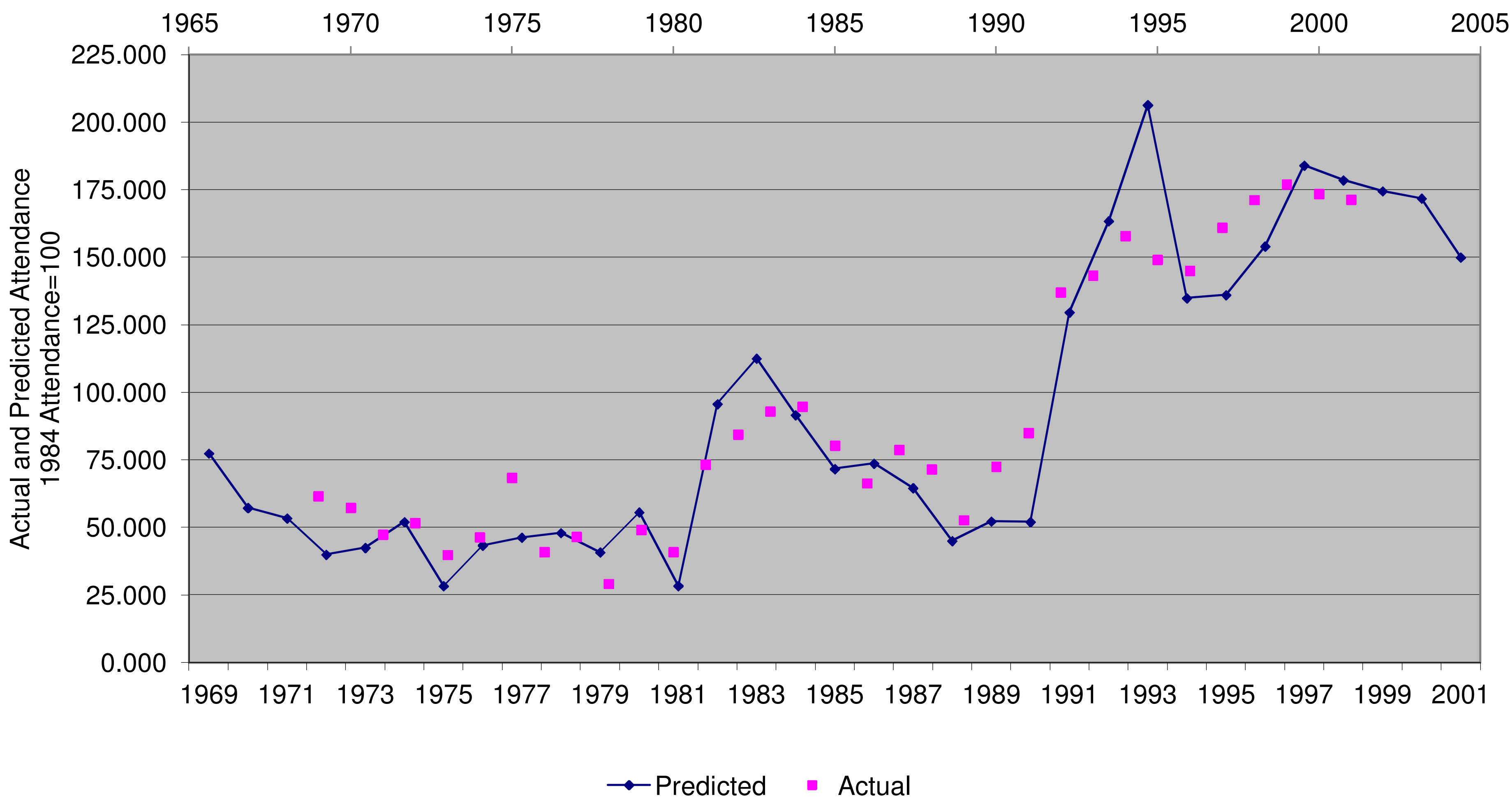

Table 2. Summary of Primary Data

Year	Annual Attendance	Attendance Index (1982-84=100)	Ticket Price	Atlanta CPI	Ticket Price Index	Average Player Salary	Salary Index 1984=100	Win-Loss Percentage
1969	1,458,320	77.476	$ 2.83	36.50	152.03	$24,909	23.81	56.40
1970	1,078,757	57.311	$ 3.04	38.60	154.42	$28,029	25.34	54.00
1971	1,006,320	53.463	$ 3.04	40.40	147.54	$31,543	27.24	49.30
1972	752,973	40.003	$ 3.04	41.60	143.29	$34,527	28.96	50.40
1973	800,655	42.537	$ 3.46	44.30	153.14	$37,606	29.62	45.00
1974	981,085	52.122	$ 3.62	49.20	144.27	$41,801	29.64	47.10
1975	534,672	28.405	$ 4.04	53.60	147.79	$46,383	30.19	55.50
1976	818,179	43.467	$ 4.04	56.10	141.20	$52,300	32.53	43.60
1977	872,464	46.351	$ 4.04	59.60	132.91	$74,000	43.32	44.00
1978	904,494	48.053	$ 4.04	63.90	123.97	$97,800	53.40	36.30
1979	769,465	40.879	$ 4.04	70.50	112.36	$121,900	60.33	43.40
1980	1,048,411	55.699	$ 4.04	80.30	98.65	$146,500	63.66	39.30
1981	535,418	28.405	$ 4.76	90.20	103.47	$196,500	76.01	51.10
1982	1,801,985	95.735	$ 4.76	96.00	97.22	$245,000	89.05	54.20
1983	2,119,935	112.626	$ 5.27	99.90	103.44	$289,000	100.94	56.30
1984	1,724,892	91.638	$ 5.27	104.10	99.26	$325,900	109.23	55.90
1985	1,350,137	71.726	$ 5.27	108.90	94.89	$368,998	118.23	48.90
1986	1,387,181	73.697	$ 5.67	112.20	99.09	$410,517	127.66	42.00
1987	1,217,402	64.677	$ 5.67	116.50	95.43	$402,579	120.57	47.00
1988	848,089	45.056	$ 6.67	120.40	108.62	$430,688	124.81	42.23
1989	984,930	52.326	$ 6.67	126.10	103.71	$489,539	135.46	34.30
1990	980,129	52.072	$ 6.67	131.70	99.30	$589,483	156.17	40.40
1991	2,140,217	126.647	$ 7.15	135.90	103.16	$845,383	217.05	40.70
1992	3,077,400	160.494	$ 8.39	138.50	118.78	$1,012,424	255.06	58.20
1993	3,884,720	203.385	$ 9.82	143.40	134.27	$1,062,780	255.59	60.46
1994	2,539,240	134.903	$ 11.84	146.70	158.25	$1,185,110	281.87	64.20
1995	2,561,831	136.103	$ 11.85	150.90	153.98	$1,071,029	247.65	62.50
1996	2,901,242	154.135	$ 13.53	156.00	170.06	$1,176,967	263.25	59.26
1997	3,464,488	184.069	$ 17.25	158.90	212.86	$1,383,578	303.81	62.35
1998	3,361,350	178.579	$ 17.25	161.20	209.82	$1,441,406	311.99	65.43
1999	3,284,901	174.518	$ 18.79	164.80	223.56	$1,720,050	364.17	63.58
2000	3,234,304	171.830	$ 20.21	170.60	232.28	$1,988,034	406.60	58.64
2001	2,823,532	150.007	$ 22.14	176.20	246.38	$2,264,403	448.41	54.32
2002	2,603,484	138.316	$ 21.70	178.20	238.77	$2,383,235	466.64	66.10
2003	2,401,084	127.563	$ 22.70	180.80	246.18	$2,555,476	493.17	62.35
2004	2,322,567	123.392	$ 22.70	183.20	242.96	$2,486,609	473.59	59.26

Pension Disclosures and the Value Relevance of Interim Financial Reports in the United States: The Case of SFAS 132R

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Abstract

This study investigates whether interim reports have become more value relevant subsequent to SFAS 132R. An increase in value relevance of interim reports is indicated by a significant increase in the earnings valuation coefficient in the post-SFAS 132R period. Our results suggest that SFAS 132R enhances the value relevance of interim reports. More specifically, the disclosures of periodic pension cost and its components, mandated by SFAS 132R, are shown to provide incremental value relevant information in the interim financial reports. Evidence is also presented supporting the claim that these interim disclosures have benefited the small, less resourceful investors; and that the information asymmetry pertaining to pension data between small and large investors has been reduced as a consequence of SFAS 132R.

These findings are of interest to the FASB and SEC; especially since SFAS 132R was promulgated against opposition that was claiming that such disclosures would be meaningless and confusing.

Keywords: SFAS 132R, net periodic pension cost disclosure; value relevance; interim financial reports.

Data Availability: Data are publicly available from sources identified in the paper.

"Interim period disclosure would better inform users about the effects of the most recent measurements on net benefit costs and would be useful to users in analyzing interim-period results."

Paragraph A49, SFAS 132 R (FASB 2003)

I. Introduction.

In 2003, members of the Financial Accounting Standards Board (FASB) discussed whether they should require better disclosure about companies' pension assets and their methods of forecasting market returns on assets. They identified several areas of pension reporting that could improve, including the frequency of detailed pension disclosures (Caplan 2003). These efforts resulted in the Board's issuance of Statement of Financial Accounting Standards No. 132 (Revised) in December 2003 (henceforth SFAS 132R). Extant research provides empirical evidence that pension information is overall relevant for valuation purposes (Landsman 1986, Barth 1991, Barth et al. 1992, Gopalakrishnan and Surgue 1993, Gopalakrishnan and Surgue 1995, Hann et al. 2007). Nevertheless, some researchers continue to argue that even though there has been an increased attention on pension practices and reporting around the issuance of SFAS 132R, investors continue to misvalue defined benefit pensions with large valuation errors in the stock of several companies (Coronado et al. 2008).

Our study examines whether the increased frequency of pension accounting disclosures brought about by SFAS 132R improved the information set investors rely upon to make valuation decisions. In particular, we investigate whether interim financial reports have become more value relevant subsequent to SFAS 132R. Under SFAS 132R, publicly traded companies should disclose interim financial reports for each period an income statement is presented, and the amount of net periodic pension cost recognized, along with the individual components of periodic pension cost. The additional disclosure requirements are underpinned by the claim that more complete information about pension and other postretirement benefit plan assets, obligations, cash flows, and net periodic benefit cost would help users of financial statements in better evaluating the market risk of plan assets, the amounts and timing of cash flows, and reported earnings. Since APB No. 28[1] requires companies to make estimates in interim reports based on conditions expected for annual period, timely interim pension disclosures can also yield insights in predicting future earnings. Therefore, one major expected effect of SFAS 132R is that the new disclosure requirements concerning the interim reports would improve their value relevance to their users, in particular to investors.

This line of thought has been corroborated by studies showing that additional disclosures benefit the users of financial statements (Gelb and Zarowin 2002) and that quarterly reports are in fact value relevant (Griffin, 2002). Botosan and Harris (2000) argue that increased disclosure frequency can enhance both the content and the timeliness of the information revealed. Parallel to Botosan and Harris (2000), we argue that if pension information is important to investors; quarterly reports would enhance timeliness because useful and more recent information is made available to them when making investment decisions. If quarterly pension information reveals seasonal trends not observable in annual data, then an increase in pension disclosure frequency also increases the content of the information provided.

On the other hand, pension accounting research examines whether pension information contained in the financial reports is value-relevant. There is evidence that investors do price the pension information disclosed in annual reports differently from non-pension information (Barth et al. 1992). Moreover, Hann et al. (2007) suggest that disaggregating income and book value numbers into their pension-related and non-pension-related components slightly improves the R^2 for both the smoothing and the fair value pension accounting methods. However, other evidence suggests that investors do not fully impound this information in setting prices. In particular, Picconi (2006) concludes that in the pre-SFAS 132R period, investors and analysts fail to fully process publicly available pension information. In the same vein, Franzoni and Marín (2006) show that the market does not value severe underfunding of pension plans properly. On another note, Butler et al. (2007) show that when an increase in reporting frequency is mandated by the SEC, the quality of financial reporting measured by the timeliness of earnings does not increase. Collectively, this stream of literature suggests that pension accounting information is only partially reflected in stock prices, and that the increased frequency mandated by the SEC might not have an effect on the value relevance of interim reports.

We add to the debate about the value relevance of pension disclosures in interim reports and explore the apparent contradiction between the SEC's intuitive argument and the findings from this stream of research. Specifically, it is our objective to investigate whether quarterly financial reports have become more value relevant subsequent to SFAS 132R. Our examination of a sample of 26,344 firm-quarter observations suggests that quarterly reports have become more value relevant from investors' perspective, and that SFAS 132R in fact improved the value relevance of quarterly reports.

Our study contributes to the pension disclosure and interim reporting literature in at least three aspects. First, it provides additional evidence on the value relevance of pension information by examining quarterly data. To our knowledge, no prior research speaks to the value relevance of pension related items using quarterly data. Second, it adds to the debate over the value relevance of interim reports. Third, our study provides evidence on the effectiveness of SFAS 132R in enhancing the value relevance of interim disclosures. On a broader note, our results could explain in part the empirical findings that there has been a particularly acute increase in the

[1] APB Opinion No. 28, Interim Financial Reporting.

proportion of annual information released during earnings announcement windows since 2004 (Ball and Shivakumar, 2008).

The paper unfolds as follows: Section 2 discusses the institutional background, prior research, and hypotheses development. Section 3 outlines our sample data and estimation model. Section 4 presents our empirical results. Finally, section 5 provides a brief discussion of the implication of our findings and a conclusion.

II. Background and Hypotheses Development

II.1 Institutional background

Pension information disclosure is a particularly relevant and timely issue to both the users of the financial statements and standard setters. Anecdotal evidence suggests that in 2006, 100 large U.S. corporations with defined benefit pension plans accounted for pension plan assets and annual pension cost of about \$1.3 trillion and \$26.4 billion respectively. In addition, pension expense constitutes an increasingly large fraction of the net income for firms with defined benefit pension plans. The significance of pensions and the need expressed by users of the financial statements for more information about economic resources and obligations related to pension plans provided compelling reasons for FASB to revise its standards pertaining to pensions accounting. In 2005 and following the suggestion of the Securities and Exchange Commission (SEC), FASB engaged in a major pensions accounting overhaul project. As a result of the first phase of this project, FASB issued SFAS 158 which requires employers to recognize overfunded or underfunded status of pension plans, <u>and record any changes in value on their balance sheets at fair value</u> (FASB 2006). For the second phase of the pensions accounting reform project, FASB is collaborating with the International Accounting Standards Board. This second phase is particularly important because it subscribes to the convergence project of the U.S. and International Accounting Standards.

Despite the timeliness and the importance of the issue, to this date, no research has examined whether SFAS 132R is effective in enhancing the value relevance of quarterly reports, although there exists some evidence on the value relevance of interim reports and pension items separately.

II.2 Value relevance of interim financial reports

The extent to which information contained in quarterly earnings announcements provides information for future earnings has been fairly discussed in the accounting literature. For example, Brown and Rozeff (1979) examine whether interim reports help improve forecasts of future quarterly earnings. They find that quarterly data has predictive value for improving forecasts of future quarterly earnings. On the other hand, Bernard and Thomas (1990) investigate and find that stock prices fail to reflect fully the implications of current quarterly earnings for future earnings. Additionally, Balsam et al. (2002) examine whether investors value the information provided in the quarterly financial statements. They find a negative association between unexpected discretionary accruals and cumulative abnormal returns over a short window around the 10-Q filing date. They also provide evidence that the reaction of sophisticated investors precedes that of unsophisticated investors, as measured by institutional holdings. Francis et al. (2002) examine the usefulness of quarterly earnings announcements and find that the value relevance of interim reports seem to have increased over time, and that the increase is due to an increase in concurrent information in the press releases of earnings announcement. The authors note that it is the earnings announcements and not the summary

earnings number itself that convey the increasing amounts of information to investors. They suggest that discussions of changes in the usefulness of financial reporting should take into account all the information that the earnings announcement press release reveals to investors, including disaggregate and forward looking earnings information.
In the same vein, Botosan and Plumlee (2002) examine the association between the frequency of disclosures and the cost of equity capital. They show that more frequent disclosures such as those in the quarterly reports are associated with higher cost of equity capital. They reason that greater timely disclosures increase the cost of equity capital possibly through increased stock price volatility. More recently, Butler et al. (2007) compare the effect of the frequency of voluntary and mandatory disclosures in the form of interim reports on the timeliness of earnings. Their findings suggest that regulation which forces firms to adopt more frequent financial reporting policies is unlikely to result in improvements in earnings timeliness to the extent achieved by firms freely choosing to report more frequently.
Overall, prior literature assessing the value relevance of interim reports suggests that while interim disclosures seem to be value relevant, investors fail to fully impound the information in establishing stock prices. Some studies suggest that increased disclosure would help curtail this limited informational value to investors (Gelb and Zarowin 2002) while some others suggest that more frequent disclosure that is voluntary is key in improving the value relevance of interim financial reports. Mandated increased frequency will not have a significant impact on financial reporting value relevance (Butler et al. 2007).

II.3 Value relevance of pension accounting information

Several studies discuss the value relevance of pension information. Barth et al. (1992) investigate whether investors price the components of pension cost differently. Their results are consistent with their predictions: investors value the pension cost components differently. Davis-Friday et al. (2005) examine whether firms use smoothed fair value methods for calculating expected return on plan assets and evaluate the effect of these methods on earnings. They also examine whether the market is able to adjust for cross-sectional differences in how firms account for the expected return component of pension expense. Their findings are mixed about whether the marker prices the difference between expected returns computed using fair values and reported expected returns. Also, Hann et al. (2007) examine the period spanning 1991 to 2002, and compare the smoothing model, which generates a stable pension expense, and the proposed fair-value model of pension accounting. They find that the joint value relevance of book value and income is significantly higher under smoothing model than under fair-value model. Similarly, Kiosse et al. (2007) evaluate the pension expense under three alternative methods (the GAAP method, the NETCOST method, and the fair-value method). They find that the GAAP model and the fair value specification including the unexpected return are more likely to provide the most accurate estimates of equity values. In the same vein, Coronado et al. (2008) investigate whether stock prices reflect the fact that investors have accurately understood the economic value of net pension assets, and not merely consider the pension accruals located on the income statement. They find that pension information is value relevant, but that the coefficient on pension EPS is overall as large as that on Core EPS (defined as EPS minus pension EPS), which suggests that investors overprice pension earnings.
Finally, Picconi (2006) examines whether investors and analysts fully process the estimable earnings effects of changes in the PBO, plan assets, discount rate, and compensation rate. He finds that investors and analysts fail to fully impound pension information in setting prices and

forecasting earnings. He provides evidence that prices reflect the pension information that has already been recognized in income but fail to reflect pension liabilities disclosed only in footnotes. The author notes that his results offer a benchmark to judge whether SFAS 132R has improved the quality of pension information provided to investors and analysts. He states that the revision increases the availability of pension information by requiring firms to extend the disclosures to the interim reports. He notes also that the revision broadens the scope of pension disclosure by requiring the disclosure of pension assumptions, breakdown of plan assets by asset class, disclosure of the accumulated benefit obligation, and a payout schedule for future benefits. Picconi (2006) predicts that the revision will enable investors and analysts to better assess the impact of a firm's pension plan on firm performance. Following this prediction, we conjecture that SFAS 132R resulted in higher value relevance of earnings in explaining firm value which leads to our first hypothesis:

H1: The earnings valuation coefficient (EVC) of the interim financial disclosures is higher for the post-SFAS 132R period than for the pre-SFAS 132R period.

Having established the incremental value relevance of interim financial disclosures in the post-SFAS 132R period, we have to establish that this incremental value relevance comes specifically from the new pension disclosures under SFAS 132R. Our second hypothesis is thus framed as follows.

H2: The incremental EVC postulated in hypothesis 1 comes from the new pension disclosures mandated by SFAS 132R.

During FASB's deliberations on SFAS 132R, many respondents disagreed with the interim period disclosure of the components of net benefit cost (see paragraph A50 of FASB 2003). They argued that since pension accounting is based on annual measurements and that these benefits are long-term, the interim disclosure of short-term components of net benefit costs is meaningless. The FASB disagreed and concluded that interim disclosure of components of net benefit cost would be useful to users of the financial statements. Our next hypothesis tests if FASB's reasoning was justified.

H3: The interim disclosure of components of net periodic pension cost mandated by SFAS 132R provides value relevant information about earnings that is incremental to the net periodic pension cost.

The SEC has stated that,

> "The laws and rules that govern the securities industry in the United States derive from a simple straightforward concept: all investors, whether large institutions or private individuals, should have access to certain basic facts about an investment prior to buying it. To achieve this, the SEC requires public companies to disclose meaningful financial and other information to the public, which provides a common pool of knowledge for all investors to use to judge for themselves if a company's securities are a good investment. Only through the steady flow of timely, comprehensive and accurate information can people make sound investment decisions," (Asthana et al. 2004).

Thus, one of the objectives of financial disclosures in the US is to level the playing field between large and resourceful investors (such as, institutions) and small and less resourceful investors. The last hypothesis we test is to see if SFAS 132R disclosures helped small investors by reducing the information asymmetry between large and small traders. Thus,

H4: The interim disclosures mandated by SFAS 132R reduced the information asymmetry between the large and small traders.

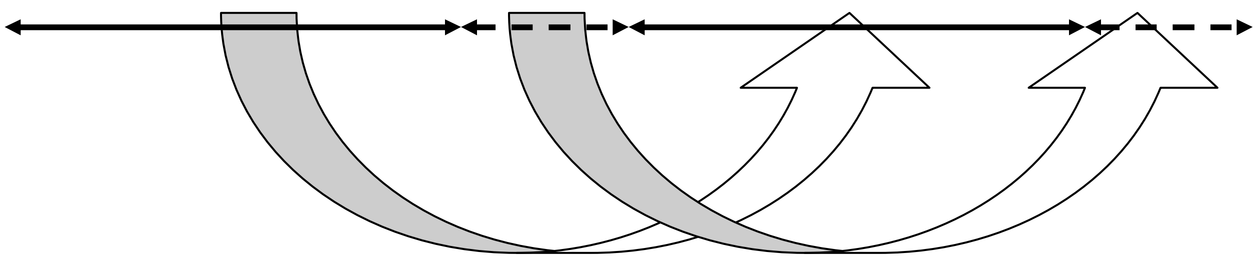
III. Research Method

III.1 Sample selection and data description

The objective of this study is to investigate whether SFAS 132R enhanced the value relevance of quarterly earnings. We collect data for all firms with December fiscal year ends available on the Compustat database. We select the quarters around December 15th, 2003 (starting from the first quarter of 2003 to the last quarter of 2004) since interim reporting under SFAS 132R became effective for interim quarters beginning after that date. We partition these quarterly observations into pre-SFAS 132R observations (four quarters of 2003) and post-SFAS 132R observations (four quarters of 2004). Figure 1 further highlights this partitioning. We eliminate observations with missing data for our tests. We further require that all eight quarters of data are available. The remaining data set consists of 26,344 firm-quarter observations relating to 3,293 unique firms. The sample selection procedure is described in Table 1.

Figure 1

Fiscal Year = 2003				Fiscal year = 2004			
Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtr 1	Qtr 2	Qtr 3	Qtr 4
No interim pension disclosures				Interim pension disclosures under SFAS 132R for quarters beginning after 12/15/2003			



Net Effect of SFAS 132R adjusted for contemporaneous trend effects
= [(Interim Quarter$_{2004}$ – Interim Quarter$_{2003}$) – (Fourth Quarter$_{2004}$ – Fourth Quarter$_{2003}$)]

Table 1: Sample Selection Procedure

Data Step	Observations Left
Compustat observations during 2003-04 period with December fiscal year-end	= 65,894
Non-Missing data for variables	= 34,861
All 8-quarters of data available (Hypothesis 1)	= 26,344†
Data for Quarters 1-3 for both years (Hypothesis 2)	= 19,758†
Data for Quarters 1-3 for 2003 (Hypothesis 3)	= 9,879†
Data for Quarters 1-3 for both years with data on institutional holdings available on Compact-Disclosure (Hypothesis 4)	= 13,002††

† These observations pertain to 3,293 unique firms.
†† These observations pertain to 2,167 unique firms.

III.2 Research design

III.2.1 Test of Hypothesis 1

In order to assess whether the value relevance of quarterly reports have changed as a result of SFAS 132R, we use a valuation-based model. We measure value relevance by the extent to which book value and earnings are related to market value. Our main specification is an Ohlson (1995) type model, with interactions of the earnings variables with an indicator variable for observations after SFAS 132R (DYR2004).

$$MVPS = \alpha_0 + \alpha_1 DYR2004 + \alpha_2 BVPS + \alpha_3 EPS + \alpha_4 EPS*DYR2004 + error \qquad (1)$$

Where:

MVPS = Market value of the firm per share at close of 90 days after quarter end

DYR2004 = Dummy variable with value of 1 for quarters in the year 2004; and 0 otherwise (thus, DYR2004 = 1 represents the post-SFAS 132R period and DYR2004 = 0 represents the pre-SFAS 132R period)

BVPS = Book value per share at the close of the current fiscal quarter

EPS = Earnings per share (diluted, excluding extraordinary items) during the current fiscal quarter

The variables used in the research design are summarized in Table 2.

Table 2: Variable Definitions (in alphabetical order)

Variable	Definition
BVPS	Book value per share at the close of the current fiscal quarter
DYR2004	Dummy variable with value of 1 for quarters in the year 2004; and 0 otherwise
EPS	Earnings per share (diluted, excluding extraordinary items) during the current fiscal quarter
EROPA	Expected return on pension assets = PPRPAQ as a percentage of PPCQ
ICOST	Pension plan interest cost = PPICQ as a percentage of PPCQ
INSTHOLD	Percentage of institutional holdings obtained from Compact-Disclosure database
LARGE	Dichotomous variable with value=1 if the percentage of institutional holdings (INSTHOLD) is greater than the median value; and 0 otherwise
LOGINST	Equals natural logarithm of (1 + INSTHOLD)
MVPS	Market value of the firm per share at close of 90 days after quarter end
PCOST	Natural Logarithm of (1 + PPCQ)
PPCQ	Periodic pension cost (net) from quarterly pension Compustat
PPICQ	Pension plan interest cost from quarterly pension Compustat
PPRPAQ	Pension plan return on plan assets from quarterly pension Compustat
PPSCQ	Pension plan service cost from quarterly pension Compustat
SCOST	Pension plan service cost = PPSCQ as a percentage of PPCQ

The change in value relevance of the interim quarter disclosures will be measured by the sign and significance of the coefficient on the interaction term between EPS and DYR2004 for a regression with only quarters 1 through 3 observations. Our first hypothesis predicts that α_4 is positive and significant. On another note, because the change in value relevance might be caused by other trends across time, unrelated to SFAS 132R, we also run equation 1 for only quarter 4 observations. Since quarter 4 in 2003 had already adopted SFAS 132R, the coefficient α_4 represents any change in the value relevance of earnings across time unrelated to SFAS 132R. If α_4 (quarters 1-3) > α_4 (quarter 4), then we can conclude that SFAS132R enhanced the value relevance of earnings, after controlling for unrelated time trends. This would support hypothesis 1.

III.2.2 Test of Hypothesis 2

For testing hypothesis 2, we use observations relating only to quarters 1, 2, and 3, since SFAS 132R does not affect quarter 4 of 2003 and 2004 differentially. For this analysis, the number of observations is reduced to 19,758 firm-quarters, representing the same 3,293 unique firms as in the previous analysis. We use the following model.

$$MVPS = \beta_0 + \beta_1 DYR2004 + \beta_2 BVPS + \beta_3 EPS + \beta_4 EPS*DYR2004 + \beta_5 EPS*DYR2004*PCOST + error \quad (2)$$

where the PCOST variable is a natural logarithmic transformation of the Compustat variable PPCQ measuring net periodic pension cost for the quarter. Rest of the variables are as defined before. Hypothesis 2 predicts that $\beta_5 \neq 0$.

III.2.3 Test of Hypothesis 3

Hypothesis 3 predicts that the components of net periodic pension cost will provide value relevant information that is incremental to the net periodic pension cost. For this test we use only data pertaining to quarter 1-3 of 2004 when the components of net periodic pension cost were disclosed for the first time under SFAS 32R. We run the following regression.

$$MVPS = \gamma_0 + \gamma_1 BVPS + \gamma_2 EPS + \gamma_3 EPS*PCOST + \gamma_4 EPS*PCOST*SCOST + \gamma_5 EPS*PCOST*ICOST + \gamma_6 EPS*PCOST*EROPA + error \quad (3)$$

Where

SCOST = Pension Plan Service Cost (Compustat item PPSCQ) as a percentage of net periodic pension cost (PPCQ)

ICOST = Pension Plan Interest Cost (Compustat item PPICQ) as a percentage of net periodic pension cost (PPCQ)

EROPA = Expected return on Pension Plan Assets (Compustat item PPRPAQ) as a percentage of net periodic pension cost (PPCQ)

Rest of the variables are as defined before.

We expect the components, SCOST, ICOST, and EROPA to provide incremental information over PPCQ (and PCOST). In other words, we predict each of γ_4, γ_5, and $\gamma_6 \neq 0$. Additionally, if each component provides unique information then we also expect $|\gamma_4| \neq |\gamma_5| \neq |\gamma_6|$.

III.2.4 Test of Hypothesis 4

Our next test looks at the differential interpretation of PCOST by small and large investors in the pre- and post-SFAS132R periods. We use the proportion of institution holdings as a proxy for the investor profile. We estimate the following model for testing hypothesis 4.

$$MVPS = \psi_0 + \psi_1 DYR2004 + \psi_2 BVPS + \psi_3 EPS + \psi_4 EPS*PCOST + \psi_5 EPS*PCOST*LARGE + \psi_6 EPS*PCOST*LARGE*DYR2004 + error \quad (4)$$

Where LARGE = 1 if the percentage of institutional holdings, INSTHOLD (obtained from Compact-Disclosure database) is greater than the median value; and 0 otherwise.[2] We also run the above regression with LOGINST = Log (1 + INSTHOLD) replacing LARGE. Since SFAS 132R required interim disclosures for the first time in the quarters 1-3 of 2004, we run equation 4 with only quarter 1-3 data, and compare information asymmetry pertaining to pension data

[2] The results are not dependant on the definition of LARGE. Use of first or third quartiles as cut-offs yields similar results.

between small and large traders (measured by ψ_5) in the pre-SFAS 132R period (measured by ψ_5) with the information asymmetry in the post-SFAS 132R period (measured by $\psi_5 + \psi_6$).[3] Thus, if SFAS 132R is effective in leveling the playing field, as claimed by FASB and SEC, then $\psi_6 < 0$ and ideally $\psi_5 = -\psi_6$, which would imply $\psi_5 + \psi_6 = 0$, that is, the information asymmetry between small and large traders had disappeared as a result of the public disclosure mandated by SFAS 132R.

IV. Results

IV.1 Descriptive statistics and univariate analysis

Table 3 outlines descriptive statistics for our sample. The mean (median) total assets for our sample are approximately \$5.84 billion (\$0.37 billion). The mean (median) market value per share is \$18.75 (\$15.62), and the mean book value per share of common stock is about \$8.81 (\$7.16). The average (median) earnings per share for our sample firms is \$0.20 (\$0.14). The periodic pension cost has an average of \$12.96 million. The three components of periodic pension cost, mainly, service cost, interest cost, and expected return on pension assets have mean values of \$11.74, 12.78, and 11.91 million, respectively. Finally, the average (median) percentage of institutional holdings is 37.65% (34.27%).

Table 3: Sample Characteristics

Variable	Mean	Median	Q1	Q3	Std. Dev.
Tot. assets (\$ bill.)	5.8399	0.3703	0.0722	1.5557	47.0050
MVPS	18.7504	15.6195	5.4500	28.1700	15.5762
BVPS	8.8090	7.1341	2.4145	13.2009	7.6973
EPS	0.1959	0.1400	-0.0100	0.3900	0.3729
PPCQ	12.9664	0	0	0.0270	1274.0000
PPSCQ	2.5539	0	0	0.0880	16.1010
PPICQ	6.0778	0	0	0.1810	44.9136
PPRPAQ	7.5262	0	0	0.1440	61.7432
PCOST	0.3421	0	0	0.0325	0.9000
SCOST	11.7355	0	0	26.0870	22.1070
ICOST	12.7752	0	0	50.0000	23.5190
EROPA	11.9072	0	0	38.2292	23.0510
INSTHOLD	37.6553	34.2712	10.3787	62.0294	28.9056
LOGINST	1.0821	0.5188	0.3756	1.4045	1.1284

IV.2 Multivariate analysis and results

IV.1.1. Results of equation 1

Table 4 (Panel A) presents pooled regressions for equation 1 separately for quarters 1-3 (column 1) and quarter 4 (column 2). The adjusted R^2 of column 1 regression is 61.57%, and the overall significance of the model is very high (Probability > F less than 0.0001). The coefficients on the variables are all significant at the 1% level. The coefficients on BVPS and EPS load positively as expected. While the coefficient α_3 on the variable EPS represents the earnings valuation coefficient for the three interim quarters before the adoption of the statement, during 2003, the sum of the coefficients on EPS and the interaction term EPS*DYR2004 (α_3 and α_4 respectively) represents the earnings valuation coefficient for the interim quarters during 2004. The interim period earnings valuation coefficients are positive in both the pre- and post-SFAS 132R periods.

[3] Even though quarters 1-3 of 2003 did not require disclosure of net pension costs, SFAS 132R required that firms disclose comparative data for the prior year after adoption in quarters 1-3 of 2004.

The earnings valuation coefficient increased from about 14.14 pre-SFAS 132R to about 16.93 in the period after the adoption. The coefficient on the interaction term EPS*DYR2004 represents the differential value relevance between the pre- period and the post- period. It is positive and significant (α_7 = 2.78, p value < 0.0001), which proves that after the adoption of SFAS 132R there is a better association between the market value and earnings. This result supports our first hypothesis that the value relevance of earning increased subsequent to the adoption of the statement.

Table 4: Mutivariate analysis of incremental value relevance of interim disclosures under SFAS 132R

Panel A: Test on Earnings Valuation Coefficients

$$MVPS = \alpha_0 + \alpha_1 DYR2004 + \alpha_2 BVPS + \alpha_3 EPS + \alpha_4 EPS*DYR2004 + error$$

Variable	Coefficient	Exp. Sign	Quarters 1 - 3		Quarter 4	
			Estimate (Column 1)	p Value	Estimate (Column 2)	p Value
Intercept	α_0	?	***5.9638	<0.0001	***7.2337	<0.0001
DYR2004	α_1	?	***0.9660	<0.0001	**-0.5569	0.0436
BVPS	α_2	+	***1.0206	<0.0001	***1.1639	<0.0001
EPS	α_3	+	***14.1444	<0.0001	***11.5503	<0.0001
EPS*DYR2004	α_4	+	***2.7837	<0.0001	-0.0328	0.9558
No. of Observations			19,758		6,586	
Adjusted R^2			0.6157		0.6099	
F value			7915.34		2574.34	
Probability > F			<0.0001		<0.0001	
t-Statistics {α_4(Column 1) – α_4(Column 2)}				***4.33		
Highest VIF			2.6035		2.6513	
White's χ^2			785.14		306.64	
Probability > χ^2			<0.0001		<0.0001	

Table 4 (continued)

Panel B: Test on Explanatory Power

$$MVPS = \alpha_0 + \alpha_1 BVPS + \alpha_2 EPS + error$$

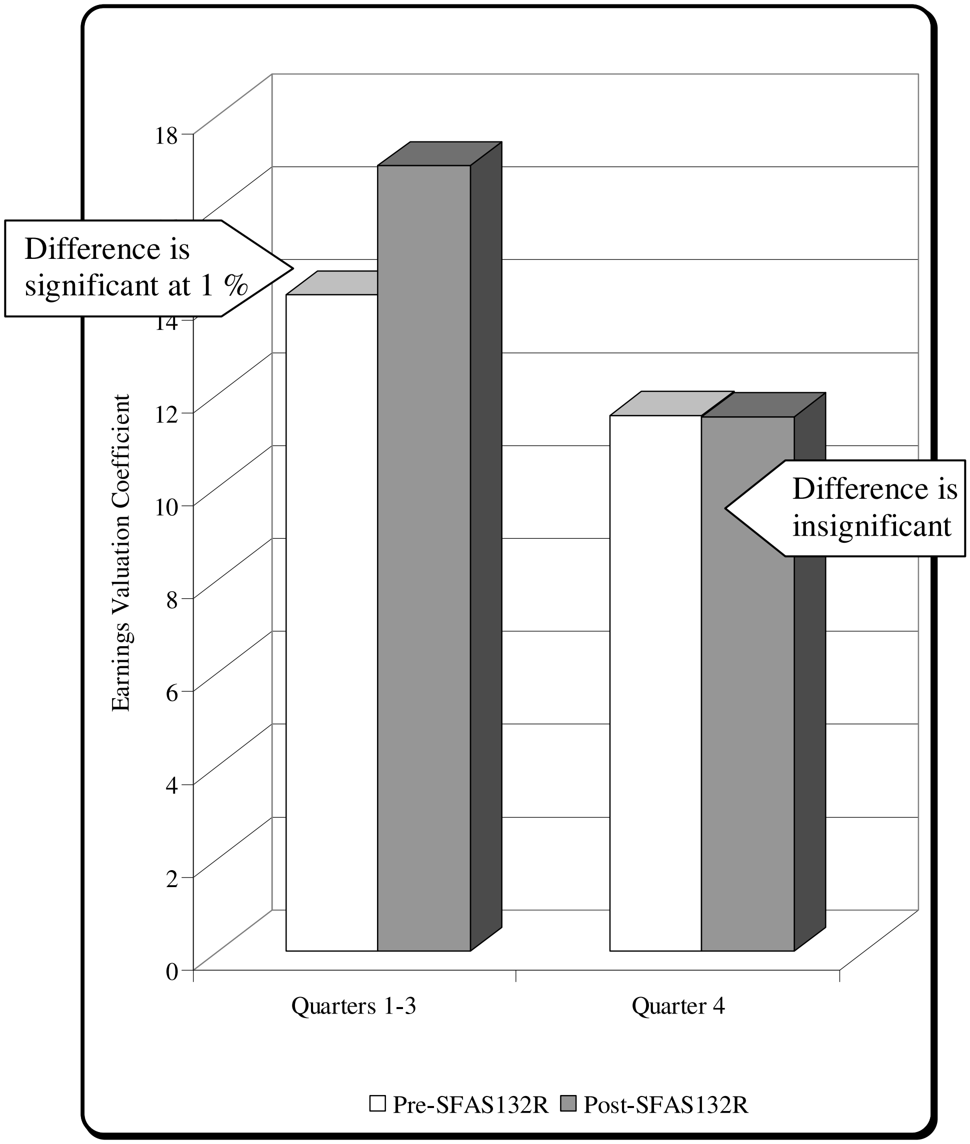
Quarter	Period	BVPS	EPS	Observations	Adj. R-Square	Vuong's Statistics
Interim	2003	***0.9825	***14.6291	9,879	0.5992	***2.9001
	2004	***1.0577	***16.4215	9,879	0.6250	
Fourth	2003	***1.1495	***11.6994	3,293	0.6080	0.1550
	2004	***1.1772	***11.3727	3,293	0.6112	

See Table 2 for variable definitions.
Significance levels are one-sided where direction can be predicted; two-sided otherwise.
*** implies significance at 1% level; ** implies significance at 5% level

While this result provides evidence that the value relevance of earnings increased post-SFAS 132R, we cannot exclude the possible confounding effects of other contemporaneous factors. It is possible that the expected results are due to a history effect (a time trend), and that the higher EVC is a mere artifact of the increasing value relevance reported in prior literature (Francis et al. 2002). To ensure that our results are not the byproduct of other unrelated phenomena, we re-estimate equation 1 with observations only in the fourth quarter. Our results (column 2) suggest that the value relevance of earnings for quarter 4 remains unchanged after the adoption of SFAS 132R, since the interaction term EPS*DYR2004 is insignificant (-0.03; p value = 0.9558). A test of [α_4 (column 1) - α_4 (column 2)] returns a t statistics of 4.33 that is significant at 1% level that confirms that the interim quarter increase in EVC cannot be explained by other non-SFAS 132R effects, such as time-trend. The comparative changes in EVC for the interim quarters and quarter 4 during the pre- and post-SFAS 132R periods are further exhibited in Figure 2.

In addition to the above interaction model that tests for changes in EVC, we also conduct additional tests on the changes in the explanatory power of the Ohlson's (1995) model separately for the interim and fourth quarters. These results are reported in Panel B of Table 4. As expected, the explanatory power of the model for interim quarters increased from 59.92% to 62.50% after the adoption of SFAS 132R. This increase is significant at 1% level with a Vuong's (1989) statistics of 2.9001. However, the same statistics for the fourth quarter is insignificant. These findings further support the conclusions in Panel A above.

Figure 2: Plot of EVC before and after the adoption of SFAS 132R



IV.1.2. Results of equation 2

Table 5 outlines our results for hypothesis 2. Since this test pertains to quarters 1-3, we exclude quarter 4 observations from the test. The coefficients on all variables for both specifications (columns 1 and 2) are all positive and significant at the 5% level or better. In particular, the coefficient on EPS*DYR2004 is equal to 2.79, which shows that the earnings valuation coefficient increased from 14.13 to 16.92. The increment of 2.79 is significant at 1% level.

Table 5: Role of net periodic pension cost in the SFAS-132R related incremental value relevance

$MVPS = \beta_0 + \beta_1 DYR2004 + \beta_2 BVPS + \beta_3 EPS + \beta_4 EPS*DYR2004 + \beta_5 EPS*DYR2004*PCOST + error$

Variable	Coefficient	Exp. Sign	Estimate (Column 1)	p Value	Estimate (Column 2)	p Value
Intercept	β_0	?	***5.9544	<0.0001	***5.9554	<0.0001
DYR2004	β_1	?	***0.9525	<0.0001	***0.9602	<0.0001
BVPS	β_2	+	***1.0221	<0.0001	***1.0220	<0.0001
EPS	β_3	+	***14.1254	<0.0001	***14.1275	<0.0001
EPS*DYR2004	β_4	+	***2.7951	<0.0001	**0.8605	<0.0155
EPS*DYR2004*PCOST	β_5	$\neq 0$			***3.4997	<0.0001
No. of Observations			19,758		19,758	
Adjusted R^2			0.6157		0.6208	
F value			7895.43		6453.49	
Probability > F			<0.0001		<0.0001	
Highest VIF			2.5987		2.6269	
White's χ^2			784.74		812.83	
Probability > χ^2			<0.0001		<0.0001	

See Table 2 for variable definitions.
Significance levels are one-sided where direction can be predicted; two-sided otherwise.
*** implies significance at 1% level
** implies significance at 5% level

When we include the variable PCOST, the coefficient on the interaction term EPS*DYR2004 drops to 0.86 (from 2.79 for the first specification) and becomes less significant (p-value = 0.0155). This represents a sharp drop of almost 70% in the coefficient of EPS*DYR2004. What is interesting to notice also is that the interaction term EPS*DYR2004*PCOST in column 2 has a positive and highly significant coefficient (about 3.5)[4]. Thus, almost 70% of the gain in EVC in the post SFAS 132R period is explained by the periodic pension cost that was disclosed for the first time in interim quarters pursuant to SFAS 132R. This result suggests that the gain in EVC in the quarterly reports after the adoption of SFAS 132R arises from the additional pension

[4] Even though we do not predict a sign for β_5, the significantly positive value needs an explanation. Note that EPS is measured net of pension costs. Thus a positive coefficient on *PCOST* interaction implies that the market is assigning a weight lower than β_4 to pension expense when valuing the firm. In other words, the investors are skeptical about pension costs. One reason could be that this number is based on actuarial estimates and managers are known to manipulate them with the intent of managing earnings (Asthana 2008). To further confirm this conjecture, we estimate the following regression:

*MVPS = ***6.5549 + ***1.0660 BVPS + ***14.2008 ADJEPS - ***9.9399 PCOSTPS*

Where *ADJEPS* is the adjusted *EPS* without the pension costs and *PCOSTPS* is the pension cost (*PPCQ*) per share. The absolute value of the coefficient of *PCOSTPS* is less than that of *ADJEPS* (F=32.44; p < 0.0001), implying that one dollar of pension cost is valued lower than non-pension revenues and expenses.

disclosures required by FASB, thus, supporting hypothesis 2.

IV.1.3 Results of equation 3

Hypothesis 3 is tested with regression 3. Since we are testing the incremental value relevance of the components of net periodic pension cost over the net periodic pension cost disclosed in the interim quarters pursuant to SFAS 132R, we confine the test to 9,879 observations for quarters 1 to 3 in 2004 when SFAS 132R related interim disclosures were made for the first time. The results are presented in Table 6.

Table 6: Incremental value relevance of the components of net periodic pension cost

$$MVPS = \gamma_0 + \gamma_1 BVPS + \gamma_2 EPS + \gamma_3 EPS*PCOST + \gamma_4 EPS*PCOST*SCOST + \gamma_5 EPS*PCOST*ICOST + \gamma_6 EPS*PCOST*EROPA + error$$

Variable	Coefficient	Exp. Sign	Estimate (Column 1)	p Value	Estimate (Column 2)	p Value
Intercept	γ_0	?	***6.6820	<0.0001	***6.6864	<0.0001
BVPS	γ_1	+	***1.0607	<0.0001	***1.0607	<0.0001
EPS	γ_2	+	***14.4606	<0.0001	***14.3189	<0.0001
EPS*PCOST	γ_3	$\neq 0$	***3.4991	<0.0001	*1.5505	<0.0522
EPS*PCOST*SCOST	γ_4	$\neq 0$			**0.0641	<0.0367
EPS*PCOST*ICOST	γ_5	$\neq 0$			***0.1940	<0.0017
EPS* PCOST*EROPA	γ_6	$\neq 0$			***-0.2173	<0.0001
No. of Observations			9,879		9,879	
Adjusted R^2			0.6344		0.6352	
F value			5686.97		2852.99	
Probability > F			<0.0001		<0.0001	
Highest VIF			1.8441		1.8594	
White's χ^2			428.90		455.91	
Probability > χ^2			<0.0001		<0.0001	

See Table 2 for variable definitions.
Significance levels are one-sided where direction can be predicted; two-sided otherwise.
*** implies significance at 1% level
** implies significance at 5% level
* implies significance at 10% level

Coefficients of BVPS and EPS are positive at 1% level. Column 1 reports the results without the components of pension cost while column 2 adds these components. Coefficient of EPS*PCOST is 3.4991 (p-value < 0.0001). The value is very close to that of EPS*DYR2004*PCOST in column 2 of Table 5. This is consistent with PCOST providing additional value relevant information about EPS, as predicted by hypothesis 2. In column 2, we add the three components of pension cost, mainly, SCOST, ICOST, and EROPA. The coefficients on EPS*PCOST*SCOST and EPS*PCOST*ICOST are positive and significant at 5% level or better, while coefficient of EPS*PCOST*EROPA is significant and negative at 1% level. The positive coefficients on the first two cost components are consistent with the reasoning discussed in footnote 2. The negative coefficient on EPS*PCOST*EROPA is consistent with the market evaluating the expected return on pension assets with a lower weight than other revenues. Thus, the investors are skeptical about the persistence of these returns. This is consistent with the finding in Asthana (2008) that managers' use expected returns on pension assets to manipulate earnings. The significant coefficients on the three components of pension cost suggest that these provide information about value relevance that is incremental to periodic pension cost. Moreover, the test $|\gamma_4| = |\gamma_5| = |\gamma_6|$ is rejected (F = 4.92; p value = 0.0073), suggesting that each component provides unique value relevant information. Also, the coefficient on EPS*PCOST declines from 3.4991 (column 1) to 1.5505 (column 2), a 56% drop, suggesting that the majority of information in PCOST comes from the three components, SCOST, ICOST, and EROPA. This supports hypothesis 3. This also supports FASB's decision to mandate interim disclosure of components of periodic pension costs despite large scale opposition (see paragraph A50 of FASB 2003).

IV.1.4 Results of equation 4

Results of estimating equation 4 are reported in Table 7. Hypothesis 4 suggests that enhanced pension disclosure under SFAS 132R should reduce the information asymmetry between small and large traders. Two versions of the regression are reported:

Column 1 with the dichotomous variable LARGE and column 2 with the continuous variable LOGINST. Both versions have adjusted r-squares over 59% with p values < 0.0001. All the variables have the predicted signs in both versions.

Table 7: Impact of SFAS 132R on the information asymmetry between small and large traders

$$MVPS = \psi_0 + \psi_1 DYR2004 + \psi_2 BVPS + \psi_3 EPS + \psi_4 EPS{*}PCOST + \psi_5 EPS{*}PCOST{*}LARGE + \psi_6 EPS{*}PCOST{*}LARGE{*}DYR2004 + error$$

Variable	Coefficient	Exp. Sign	Estimate (Column 1)	p Value	Estimate (Column 2)	p Value
Intercept	ψ_0	?	***7.4114	<0.0001	***7.4125	<0.0001
DYR2004	ψ_1		***0.9911	<0.0001	***0.9997	<0.0001
BVPS	ψ_2	+	***0.9237	<0.0001	***0.9232	<0.0001
EPS	ψ_3	+	***15.0114	<0.0001	***15.0327	<0.0001
EPS*PCOST	ψ_4	+	***3.5239	<0.0001	***4.4193	<0.0001
EPS*PCOST*LARGE	ψ_5	+	***1.4591	<0.0001		
EPS*PCOST*LARGE*DYR2004	ψ_6	–	***-1.4194	<0.0001		
EPS*PCOST*LOGINST	ψ_5	+			***2.5714	0.0003
EPS*PCOST*LOGINST*DYR2004	ψ_6	–			**-4.5513	0.0220
No. of Observations			13,002		13,002	
Adjusted R^2			0.5988		0.5983	
F value			3,234.93		3,228.15	
Probability > F			<0.0001		<0.0001	
Highest VIF			1.8074		3.7420	
White's χ^2			379.21		387.85	
Probability > χ^2			<0.0001		<0.0001	
Probability > F (Null: $\psi_5 + \psi_6 = 0$)			0.2673		0.4347	

See Table 2 for variable definitions.
Significance levels are one-sided where direction can be predicted; two-sided otherwise.
*** implies significance at 1% level; ** implies significance at 5% level

Prior to SFAS 132R, there was no pension disclosures in the interim financial reports. Since pension data is known to be value relevant, resourceful investors (such as, institutional investors) should be willing to spend money to get this information from private sources. However, smaller investors would not be able to access this information to the same extent due to lack of resources. Thus, there should be information asymmetry between these two categories of investors in the pre-SFAS 132R period. Consistent with this argument, the coefficient of EPS*PCOST*LARGE and EPS*PCOST*LOGINST are both significantly positive. In the period after the adoption of SFAS 132R, the pension information is publicly available and the advantage gained by large traders from obtaining this information from private sources is reduced. Again, consistent with this story, the coefficients on EPS*PCOST*LARGE*DYR2004 and EPS*PCOST*LOGINST*DYR2004 are both significantly negative. Moreover, the sum of coefficients on EPS*PCOST*LARGE and EPS*PCOST*LARGE*DYR2004 and the sum of coefficients on EPS*PCOST* LOGINST and EPS*PCOST* LOGINST *DYR2004 are both equal to zero (Probability > F = 0.2673 and 0.4347, respectively). This confirms that the information asymmetry between small and large traders has declined after the adoption of SFAS 132R. This finding supports hypothesis 4.

IV.1.5 Regression Diagnostics

The Belsley et al. (1980) test for multicollinearity is conducted on regression models 1, 2, 3, and 4 which are reported in tables 4, 5, 6, and 7. The highest variance inflation factor is 3.7420, below the critical level of 10. Therefore, multicollinearity does not appear to be a significant problem in any of the regression estimations. White's (1980) test for heteroskedasticity is conducted on all the regressions. The null of homoskedastic errors is rejected in all regressions. Heteroskedasticity corrected t- statistics do not alter the conclusions and are not reported. Diagnostic tests are also conducted for all regressions with influential outliers being removed based on the procedure outlined in Belsley et al. (1980). Using SAS, the studentized residual (RSTUDENT) for each observation is calculated. Any observation with an absolute RSTUDENT greater than 2 is deemed to be an influential outlier and deleted (see Belsley et al. 1980, 28). Removal of outliers does not change the conclusions presented.[5] Thus the results do not appear to be driven by outliers.

V. Conclusion

FASB issued SFAS 132 and 132R "in response to concerns expressed by users of financial statements about their need for more information about pension plans…Users of financial statements cited the significance of pensions for many entities and the need for more information about economic resources and obligations related to pension plans as reasons for requesting this additional information." One of the additional disclosures required by FASB was the components of net periodic pension cost during interim periods. The purpose of the current study is to answer the research question whether disclosing pension data in interim quarters helps investors assess the future cash flow stream, and hence the value of the firm, more efficiently, thereby, achieving the stated goal of FASB (2003) to "better inform users about the most recent measurements on net benefit cost." The findings confirm this claim from FASB. We report results that the earnings number has become more value relevant in the interim quarters subsequent to the adoption of SFAS 132R and that the newly mandated disclosures of net periodic pension cost and its components have enhanced investors ability to predict future cash flows from current quarterly earnings. We also document evidence supporting the claim that these interim disclosures have mostly benefited the small, less resourceful investors; and that the information asymmetry pertaining to pension data between small and large investors has been reduced.

A possible extension of this paper consists in examining the informativeness of quarterly earnings for future earnings (Tucker and Zarowin, 2006). FASB suggests that SFAS 132R is expected to improve the quality of earnings. Thus, it is expected that this statement improves quarterly earnings informativeness and predictability for future earnings and cash flows. On another note, recently, FASB promulgated SFAS 158 (FASB 2006) that requires employers to recognize the overfunded or underfunded status of their defined benefit postretirement plans

[5] Deleting influential observations using DFBETAS or DFFITS (Belsley et al. 1980) does not affect the results either.

(other than multiemployer plans) as an asset or liability in their statement of financial position and to recognize changes in that funded status in the year in which the change changes occur through comprehensive income of a business entity. Even though SFAS 158 --which is effective for fiscal years ending after December 15, 2006-- does not affect the interim disclosures of net periodic pension costs examined in the current paper, it mandates recognition of the funded position of postretirement plans. An interesting research question would be to see if the move to recognition from disclosure in the footnote has made the pension information more informative and value relevant.

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Appendix

Components of Net Periodic Pension Cost

The net periodic pension cost or pension expense of defined-benefit pension plans consists of service cost, interest cost, amortization of unrecognized prior service cost, amortization of experience loss (gain), minus expected return on pension assets. The service cost is the expense caused by the increase in projected benefit obligations (PBO) payable to the employees as a result of service rendered during the year. The interest cost is the interest payable on the beginning balance of PBO. Unrecognized prior service costs are additional pension benefits granted for service performed in prior periods. Experience loss (gain) is the deviation of actual amounts from estimated amounts (amortized only if they exceed 10% of the greater of PBO or market-related value of pension assets at the beginning of the year). The expected return on pension assets is the rate of expected return on pension assets multiplied by the market-related value of pension assets at the beginning of fiscal year.

Are Bankruptcy Prediction Models Useful to Auditors in Assessing Going Concern Status? Evidence from U.S. Firms

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Abstract

In the context of going-concern audit opinions, the purpose of this research paper is to: (1) examine whether there are differences in the three main bankruptcy prediction models used in prior auditing research to measure financial distress, and, (2) examine whether the relationship between financial distress (as measured using bankruptcy prediction models) and going-concern audit opinions is linear for all levels of financial distress. We find that the relationship between financial distress and the probability of receiving a going-concern opinion is not linear, as is assumed in prior studies. Rather, we find that the positive relationship between financial distress and going-concern opinions applies only for certain levels of financial distress. These results have implications in the interpretation of previous auditing research that has incorporated variables for financial distress, as well as implications for the auditing profession and for the design and interpretation of future research.

Key Words: Going Concern, Bankruptcy Prediction Models, Audit Errors, Financial Distress

I. Introduction.

As part of every financial statement audit, auditors are required to evaluate whether there is substantial doubt about their client's ability to continue as a going concern for a reasonable period of time.[6] The auditor's evaluation of going concern is based on his or her knowledge of relevant conditions and events that exist at, or have occurred prior to, the date of the auditor's report. If the auditor determines that there is substantial doubt about the entity's ability to continue as a going concern, the auditor must disclose this evaluation in an explanatory paragraph in the audit report.

During the audit, the auditor may identify certain conditions that indicate there could be substantial doubt about the entity's ability to continue as a going concern. For example, the auditor may consider such things as: noncompliance with statutory capital requirements, work stoppages or other labor difficulties, uneconomic long-term commitments, legal proceedings, loss of a key license or patent, loss of a principal customer or supplier, uninsured or underinsured losses, etc. But most importantly, the auditor should consider the currently existing financial condition of the client. One such condition the auditor may consider in evaluating going concern status is the "financial distress" of the company, which can be identified, among other ways, using "n*egative trends*—for example, recurring operating losses, working capital deficiencies, negative cash flows from operating activities, adverse key financial ratios." [7]

To the extent that "financial distress" can be estimated using currently existing bankruptcy prediction models, these models may be useful to the auditor is assessing going-concern status. In fact, the "probability of bankruptcy" (as measured using one or more bankruptcy prediction models) has been used as a control variable in prior accounting research examining going concern audit opinions.

Prior accounting research has examined variables associated with the likelihood of auditor's issuing a going-concern audit opinion for corporate clients that subsequently declare bankruptcy. (Failure of the auditor to issue a going concern opinion for a client that subsequently declares bankruptcy is defined as a Type II audit error). For example, Geiger and Rama (2006) use the following logistic regression model to examine whether Big4 audit firms (as compared to smaller, non-Big4 firms) have significantly lower Type II audit errors:

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[6] AU Section 341, "The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern," PCAOB auditing standards.

[7] AU Section 341, paragraph 6.

$$PROB(GC_{bank}) = \beta_0 + \beta_1 \, DISTRESS + \beta_2 \, LNSL + \beta_3 \, BLAG + \beta_4 \, RLAG + \beta_5 \, BIGN + \beta_6 \, DFLT + \beta_7 \, EXCH + e_{gc} \quad (1)$$

where:

GC_{bank}	=	1 if audit report contained a going-concern opinion, 0 otherwise
DISTRESS	=	variable measuring level of financial distress
LNSL	=	natural log of sales (in thousands of dollars)
BLAG	=	square root of the number of days from the audit report to the bankruptcy
RLAG	=	square root of the number of days from the fiscal yr. end to the audit report
BIGN	=	1 if audit firm was from the BigN, 0 otherwise
DFLT	=	1 if firm is in payment default, 0 otherwise
EXCH	=	1 if firm is listed on NYSE or AMEX, 0 otherwise
e_{gc}	=	error term

The variable of interest in the Geiger and Rama (2006) study was "LNSL," and was used to measure the significance of the relationship between audit firm size and the probability of issuing a going-concern audit opinion. The "DISTRESS" variable was a control variable used to control for the level of financial distress of the firm receiving the audit opinion. For their particular study, Geiger and Rama measured "DISTRESS" using a financial stress score calculated using the Zmijewski (1984) bankruptcy probability model.

Numerous auditing research studies examining going-concern audit opinions have used a similar regression model to that above, and have usually included a control variable measuring the level of "financial distress" faced by the firm when receiving the audit opinion. The inclusion of the control variable is based on research indicating that there is a significant relationship between the level of financial distress and the likelihood of receiving a going-concern audit opinion. Intuitively, and supported by prior research, is the hypothesis that the higher the level of financial distress (as measured using a bankruptcy prediction model), the higher the probability of receiving a going-concern audit opinion. Therefore, a control variable is included in the regression models to control for the level of financial distress so that the effect of other variables of interest can be examined (such as firm size in the Geiger and Rama (2006) study).

However, there are two significant limitations in prior research related to their use of a control variable for "financial distress." First, prior studies have used different bankruptcy prediction models to estimate "DISTRESS" when constructing their regression models. Geiger and Rama (2006), and many other studies, measure distress using the Zmijewski (1984) bankruptcy probability score. But other studies, using similar regression models, have measured distress using either the Hopwood et al. (1994) bankruptcy probability score or the Altman Z-score, Altman (1968). Likewise, auditors themselves may calculate a "probability of bankruptcy" using one of these three bankruptcy probability models when assessing the financial distress of their client. But research is limited in evaluating differences in explanatory power between these three bankruptcy probability scores in assessing going-concern status.

A second limitation in prior research is the assumption that the relationship between going-concern status and financial distress is linear for all levels of financial distress. It is possible, however, that while bankruptcy probability models may be useful in assessing going-concern status, that usefulness may vary depending on the underlying level of financial distress.

The purpose of this research paper is to: (1) examine whether there are differences in explanatory power between the three alternative measures of financial distress used in prior auditing research[8] and, (2) examine whether the relationship between financial distress and going-concern opinions is linear for all levels of financial distress. If the relationship is non-linear, results will help address the overall research question: "Are Bankruptcy Prediction Models Useful to Auditors in Assessing Going Concern Status?" These results have potential benefits in the following areas: (1) provide the auditing profession with empirical evidence regarding the usefulness of "bankruptcy prediction models" in estimating financial distress when assessing going-concern status of clients, (2) add to the interpretation of previous auditing research studies that have incorporated variables for financial distress, and, (3) add support for the design and interpretation of future research.

II. Bankruptcy Probability Models in Prior Auditing Research.

Prior research studies in auditing which examine issues related to the auditor's propensity to issue a going-concern audit opinion usually control for the firm's level of "financial distress." Typically, one of three alternative variables is used as a measure, or proxy, for the level of financial distress; Altman's Z-score, Altman (1968), the Hopwood et al. (1994) bankruptcy probability score, or the Zmijewski (1984) bankruptcy probability score.

Altman Z' Score is calculated as follows: Z = .717 (working capital / total assets) + .847 (retained earnings / total assets) + 3.107 (earnings before interest and taxes / total assets) + .420 (stockholder's equity / total liabilities) + .998 (sales / total assets). Auditing studies that have used Altman's Z-score as a measure of financial distress include Reynolds and Francis (2000) and Callaghan et al. (2009).

Zmijewski's (1984) bankruptcy probability score is calculated as follows. First, raw scores are calculated using the components of the Zmizewski et al. (1984) model: intercept of -4.803 – 3.599 (net income / total assets) + 5.406 (total liabilities / total assets) - .100 (current assets / current liabilities). PROB–Z is then calculated as F(Y), where F(.) is the distribution of the standard normal variable. Auditing studies that have used the Zmijewski (1984) bankruptcy probability score as a measure of financial distress include Geiger and Rama (2006), Geiger, Ramhunandan and Rama (2006), Robinson (2008), Francis and Krishnan (2002), and Carey, Geiger and O'Connell (2008).

Finally, the Hopwood et al. (1994) bankruptcy probability score is calculated as follows. First, raw scores were calculated using the components of the Hopwood et al. (1994) model: intercept of -7.322 – 15.756 (net income / total assets) + .973 (current assets / sales) – 1.677 (current assets / current liabilities) + 5.985 (current assets / total assets) - 9.145 (cash / total assets) + 4.224 (long term debt / total assets) + .214 (natural log of sales). PROB–H is then calculated as F(Y), where F(.) is the distribution of the standard normal variable. Auditing studies that have used the Hopwood et al. (1994) bankruptcy probability score include Myers, Schmidt and Wilkins (2008), Fargher and Jiang (2008), Geiger and Rama (2003), Carey, Kortum and Moroney (2007), and Geiger and Raghunandan (2001).

III. Current Hypotheses

The current study directly addresses the two weaknesses discussed in the introduction as they relate to the common use of a "financial distress" variable in going-concern auditing research. Specifically, we address: (1) whether the choice of the bankruptcy prediction model used to

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[8] Again, "financial distress" variables used in prior auditing research have been generally calculated using one of the following bankruptcy prediction models; Altman's Z-score, Altman (1968), the Hopwood et al. (1994) bankruptcy probability score, or the Zmijewski (1984) bankruptcy probability score.

measure financial distress affects the statistical significance of the financial distress variable, and, (2) whether the relationship between financial distress and the likelihood of a going-concern opinion is constant (or linear) for all levels of financial distress.

As a starting point, and based on a consensus in prior research, we assume that the level of financial distress is positively and significantly related to the propensity of an auditor to issue a going concern audit opinion. However, we begin by replicating prior research to test this assumption. This replication of prior research serves as a starting point in the confirmation of the relationship between financial distress and the propensity to issue a going-concern opinion, and then allows me to address the two main research questions previously listed. Thus, the initial research question is: Does the level of a firm's financial distress affect the auditor's propensity to issue a going concern audit opinion? In null form, the initial hypothesis is:

$H0_0$: The level of a firm's financial distress is not related to the auditor's propensity to issue a going concern audit opinion.

As discussed in the previous section, prior going-concern audit research studies have used three main alternative measures of "financial distress." This leads to the first of our two main research questions: Does the selection of the measure for "financial distress" affect whether the variable for financial distress is significant? In null form, the first hypothesis is:

$H0_1$: The choice of variable used to measure financial distress [the Zmijewski (1984) model, the Hopwood et al. (1994) model, or Altman's Z-score, Altman (1968)], does not affect whether the coefficient for the financial distress variable is significant.

Finally, a second limitation of prior research is an assumption that the effect of financial distress (i.e., the DISTRESS variable in model (1) above) is linear and applies equally to all levels of financial distress. In null form, the third hypothesis is:

$H0_2$: There is no difference in the coefficient of the financial distress variable across all levels of financial distress.

These hypotheses will be tested by performing logistic regression analysis as described below.

IV. Research Methodology

Sample Selection The initial population of firms includes all public companies filing Chapter 11 bankruptcy between January 1, 1997 and December 31, 2009. For all companies, SEC filings were examined to determine the existence/non-existence of a going-concern audit opinion for the fiscal year immediately preceding the year of bankruptcy. Companies filing Chapter 11 bankruptcy are identified from annual issues of the *Bankruptcy Yearbook and Almanac*, published by New Generation Research, and supplemented by additional firms, if any, listed on the bankruptcydata.com website. For each firm in the sample, SEC filings were examined to determine the firm's auditor, audit report date, financial statement date, and the existence/non-existence of a going concern opinion for the audited financial statements for the fiscal year immediately prior to the fiscal year containing the filing of Chapter 11 bankruptcy. In particular, the SEC filings were examined to determine if the auditor had failed to issue a going concern opinion within the 12 months prior to the bankruptcy filing (a Type II audit error). Financial information obtained from the Compustat database is then used to measure necessary financial variables, including firm size and the level of "financial distress" for each company prior to bankruptcy. Based on prior research, financial distress is measured using the following three alternative variables: Altman's Z'-Score, the Hopwood et al. (1994) bankruptcy probability score, and the Zmijewski (1984) bankruptcy probability score.

Firms were eliminated if SEC filings were not available to determine the firm's auditor, audit report date, financial statement date, financial variables, and the existence/non-existence of a going concern opinion for the audited financial statements for the fiscal year immediately prior to the fiscal year containing the filing of Chapter 11 bankruptcy. Firms were also eliminated if the bankruptcy filing identified during the research period was actually the *second* bankruptcy filing within a five-year period. Sample selection results are shown in Table I.

[Insert Table I Here]

A total of 1826 companies were listed as filing bankruptcy during the research time period of January 1, 1997 through December 31, 2009. A total of 155 firms were eliminated from the sample for which SEC filings were not available to determine the necessary audit and financial related variables. Also, 49 firms were eliminated from the sample where the bankruptcy filing identified during the research period was actually the second bankruptcy filing within a five-year period. In other words, firms were eliminated if there was a previous bankruptcy filing anytime during a four-year period prior to the year of the bankruptcy filing identified during the research period. These firms were eliminated because any audit opinions issued during the research period would have been influenced by a previously filed bankruptcy. The research question of the current study is to examine each audit firm's propensity to issue a going concern opinion prior to a client's bankruptcy, and thus any existence of another previously filed bankruptcy would influence any audit opinion issued subsequent to that bankruptcy. After elimination of these firms, 1622 companies remained in the final sample. Table I summarizes these sample selection procedures, including final sample size for each year of the research period 1997 – 2009.

Research Design Hypothesis 0 examines the general relationship between financial distress and the propensity to receive a going-concern audit opinion. Accordingly, we test Hypothesis 0 using the following logistic regression model to explain the probability of a Type II audit error:

$$PROB(GC_{bank}) = \beta_0 + \beta_1\, DISTRESS + \beta_2\, LNSL + \beta_3\, BLAG + \beta_4\, RLAG + \beta_5\, BIGN + \beta_6\, DFLT + \beta_7\, EXCH + e_{gc} \qquad (2)$$

where:

GC_{bank}	=	1 if audit report contained a going-concern opinion, 0 otherwise
DISTRESS	=	variable measuring the level of financial distress
LNSL	=	natural log of sales (in thousands of dollars)
BLAG	=	square root of the number of days from the audit report to the bankruptcy
RLAG	=	square root of the number of days from the fiscal yr. end to the audit report
BIGN	=	1 if audit firm was from the BigN, 0 otherwise
DFLT	=	1 if firm is in payment default, 0 otherwise
EXCH	=	1 if firm is listed on NYSE or AMEX, 0 otherwise
e_{gc}	=	error term

The variables for LNSL, BLAG, RLAG, BIGN, DFLT and EXCH are included to control for other variables that prior research has found to also be potentially related to the propensity to issue a going-concern audit opinion, and are the variables which are also included in the Geiger and Rama (2006) model.

Hypothesis 1 is addressed by duplicating research Model (2) above using each of the following three alternative variables to measure financial distress: (1) the Zmijewski (1984) bankruptcy probability score, (2) the Hopwood et al. (1994) bankruptcy probability score, and (3) Altman's Z-score, Altman (1968).

Finally, Hypothesis 2 is addressed by examining whether the coefficient for the “distress” variable remains constant for all levels of distress, i.e., whether the relationship is linear. If it is not, then this would indicate that the relationship between financial distress and Type II audit errors depends on the underlying level of financial distress. For example, it is hypothesized that the auditor's propensity to issue a going-concern audit opinion is not affected by the level of financial distress when the level of financial distress is relatively low, and that the level of financial distress is significantly related to going-concern opinions only when the level of financial distress is above a minimum level.

V. **Results**.

The logistic regression results related to Hypothesis 0 and Hypothesis 1 are presented in Table II. Shown are the coefficients (with related Chi-square values in parentheses) for each of the variables in Model 2, including the "DISTRESS" variable measured using each of the three alternative measures for financial distress.

[Insert Table II Here]

Based on these results, the initial null hypothesis (H_0) is rejected. There is a positive and significant relationship between the level of financial distress and the probability of receiving a going-concern audit opinion. [9] This significant and positive relationship between financial distress and going-concern is consistent with prior audit research. This relationship is significant even after controlling for the effects of firm size (LNSL), auditor size (BIGN), bankruptcy time lag (BLAG), audit reporting time lag (RLAG), default status (DFLT), and exchange listing (EXCH).

Given that the results are consistent for each of the three alternative measures of financial distress, null hypothesis H_1 is also rejected. The Chi-square coefficients for the DISTRESS variable measured using Altman's Z-score, Hopwood's bankruptcy probability score and Zmijewski's bankruptcy probability score are -5.04, 5.23 and 7.91 respectively, with each significant at the .01 level. Given the similar underlying financial data used by each of the three measures, and given the similar results when each of the variables is used in the regression equation, it is likely that the results of prior research studies are not significantly affected by the choice of which "distress" variable is used. This conclusion is consistent with Geiger and Raghunandan (2002), who initially use the Hopwood et al. (1994) bankruptcy probability score in their model, but also state, "As part of sensitivity tests, we also used the model from Zmijewski (1984) to calculate the probability of bankruptcy. The results remain essentially the same when this alternative model is used."

[9] The coefficient for DISTRESS using Altman's Z-score is negative because Altman's Z-score is constructed such that a lower score equates to a higher level of financial distress. For the Hopwood and Zmijewski scores, the variables are constructed such that a higher score equates to a higher level of financial distress. Thus, in each case, the higher the level of financial distress, the higher the probability of receiving a going-concern audit opinion.

My second research question is: Does the effect of financial distress (i.e., the DISTRESS variable in model (2) above) remain linear and apply equally to all levels of financial distress? This is the assumption of prior research studies which have used a financial distress variable in their regression models. This assumption is illustrated in Figure 1.

[Insert Figure 1 Here]

However, this assumption of a linear relationship between financial distress and the probability of receiving a going-concern audit opinion has weaknesses. First, prior research has already acknowledged that auditors generally do not issue going-concern opinions for non-stressed companies; Mutchler (1985), Hopwood et al. (1994), and Geiger and Rama (2006). Thus, at low levels of financial distress, one would expect no relationship between the level of financial distress and the likelihood of receiving a going-concern. Similarly, we would argue that once a firm reaches a certain upper level of financial distress and the auditor incorporates that information into their going-concern decision, that further marginal increases in the level of financial distress would not marginally affect the auditor's decision to issue a going-concern.
In other words, we hypothesize that the relationship between financial distress and the probability of receiving a going-concern is ***not linear for all levels of financial distress***. Rather, at higher levels of financial distress, it is hypothesized that financial distress has become fully reflected in the auditor's assessment of going concern, and that above a certain level, marginal increases in financial distress become unrelated to the probability of receiving a going-concern opinion. I illustrate this hypothesis in Figure 2.

[Insert Figure 2 Here]

This hypothesis is addressed by examining whether the coefficient for the "DISTRESS" variable remains constant for all levels of distress, i.e., whether the relationship is linear. If it is not, then this would indicate that the relationship between financial distress and Type II audit errors depends on the underlying level of financial distress. Results for this analysis are presented in Tables III, IV and V.

[Insert Tables III, IV and V Here]

Table III presents the coefficients (Chi-square values in parentheses) for each of the variables in Model 2, measuring the DISTRESS variable using Altman's Z-score. The regression model was calculated separately for three different ranges of DISTRESS variable values; the lower 15% of DISTRESS values, the middle 70% of DISTRESS values, and the upper 15% of DISTRESS values. Of interest are the Chi-square values for the DISTRESS coefficients for each of the three categories of DISTRESS values. For financial distress values in category 1, (the lower 15% of DISTRESS values), the Chi-square value for the DISTRESS coefficient is -1.14, and is not statistically significant. ***In other words, for lower levels of financial distress, there is no significant relationship between the level of financial distress and the probability of receiving a going-concern audit opinion.*** This is consistent with our hypothesis as described in Figure 2.
Similarly, for financial distress values in category 3, (the upper 15% of DISTRESS values), the Chi-square value for the DISTRESS coefficient is .82, which is again not statistically significant, and is again consistent with our hypothesis as described in Figure 2. At higher levels of financial

distress, the information about financial distress has become fully reflected in the auditor's assessment of going concern, and above a certain level, marginal increases in financial distress become unrelated to the probability of receiving a going-concern opinion. For the remaining levels of financial distress (Category 2 of the DISTRESS values in Table III), the Chi-square value for the DISTRESS coefficient is -6.59, significant at the .01 level. This is consistent with our hypothesis described in Figure 2; ***that only within a certain range is financial distress positively and significantly related to the probability of receiving a going-concern audit opinion.***

Tables IV and V present the coefficients (with related Chi-square values in parentheses) for each of the variables in Model 2, measuring the DISTRESS variable using Hopwood's (1994) model (shown in Table IV) and Zmijewski's (1984) model (shown in Table V). Regardless of the measure used for financial distress, the results are again consistent: for both lower levels (Category 1) and upper levels (Category 3) of financial distress, there is no significant relationship between the level of financial distress and the probability of receiving a going-concern audit opinion; ***only within a certain range is financial distress positively and significantly related to the probability of receiving a going-concern audit opinion.***

VI. Conclusion.

Prior accounting research has examined variables associated with the likelihood of auditor's issuing a going-concern audit opinion for corporate clients that subsequently declare bankruptcy. This study has examined two limitations in that prior research related to how those studies measure "financial distress" and the assumptions in those studies related to the relationship between financial distress and the probability of receiving a going-concern audit opinion.

Using logistic regression, the current study examines the relationship between Type II audit errors and the level of financial distress. Results of this study: (a) address the limitations in prior research studies that have examined the relationship between financial distress and Type II audit errors, and, (b) provide evidence on the extent to which varying levels of financial distress affects the auditor's propensity to issue a going-concern audit opinion.

Specifically, we find that the relationship between financial distress and the probability of receiving a going-concern audit opinion is not linear. Rather, we find that at low levels of financial distress, financial distress is not relevant to the auditor's decision, and that marginal increases in financial distress (as measured using one of the three commonly used bankruptcy probability models) show no significant relationship with the probability of receiving a going-concern audit opinion. Similarly, we find that at higher levels of financial distress, the information about financial distress has already become fully reflected in the auditor's assessment of going-concern and that above a certain level, marginal increases in financial distress are again unrelated to the probability of receiving a going-concern opinion. Only within a certain range is financial distress positively and significantly related to the probability of receiving a going-concern audit opinion. These results have implications both in the interpretation of previous auditing research that has incorporated variables for financial distress, as well as implications for the design and interpretation of future research.

Table I: Summary of Sample Selection Procedures: Final Sample Size by Year

Year	Total # of Firms Filing Bankruptcy As Listed in the *Bankruptcy Yearbook* [1]	Less: Firms Missing 10K or Other SEC Filings Necessary to Determine Going Concern Status [2]	Less: Firms Filing Previous Bankruptcy Within the Prior Four-Year Period [3]	Final Sample Size
1997	83	17	2	64
1998	122	15	3	104
1999	145	15	5	125
2000	179	12	4	163
2001	263	17	6	240
2002	220	12	6	202
2003	172	8	8	156
2004	92	19	4	69
2005	86	11	4	71
2006	66	4	2	60
2007	78	8	0	70
2008	127	10	1	116
2009	193	7	4	182
Total	1826	155	49	1622

1 Annual issues of the *Bankruptcy Yearbook and Almanac*, New Generation Research, Inc., supplemented by firms listed on BankruptcyData.Com, a division of New Generation Research.

2 Firms were eliminated from the sample if no SEC filings were available to determine the auditor, audit opinion, audit report date and financial statement date for the audited financial statements for the fiscal year immediately preceding the fiscal year containing the filing of Chapter 11 bankruptcy.

3 Firms were eliminated from the sample where there was a previous bankruptcy filing anytime during a four-year period prior to the bankruptcy filing.

Table II: Logistic Regression Results Using Alternative Measures of Financial Distress

Model [1]: $GC = \beta_0 + \beta_1$ DISTRESS $+ \beta_2$ LNSL $+ \beta_3$ BLAG $+ \beta_4$ RLAG $+ \beta_5$ BIGN $+ \beta_6$ DFLT $+ \beta_7$ EXCH

	Logistic Results for Alternative Measures of Financial Distress		
Variable	Altman's Z Score	Hopwood, et. al. (1994)	Zmijewski, et. al. (1984)
Intercept	23.5971 (8.46) *	7.6626 (6.94) *	3.2554 (2.57) *
DISTRESS	-28.8582 (-5.04) *	4.3439 (5.23) *	14.6084 (7.91) *
LNSL	-.3010 (-6.36) *	-.3589 (-7.92) *	-.3779 (-8.67) *
BLAG	-.1935 (-11.31) *	-.1908 (-11.24) *	-.1895 (-10.94) *
RLAG	.0414 (1.28)	.0366 (1.14)	.0215 (.65)
BIGN	-.3314 (-1.80)	-.3599 (-1.96) *	-.2678 (-1.43)
DFLT	.3418 (1.40)	.3958 (1.60)	.3305 (1.31)
EXCH	-.1153 (-.69)	-.1321 (-.79)	.0212 (.12)

1 Variables as defined in the body of this paper.
* Significant at the .05 level. Chi-square values in parentheses.

Figure 1

Assumption in Prior Studies:
Relationship Between the Level of Financial Distress and the Probability of Receiving a Going Concern Audit Opinion

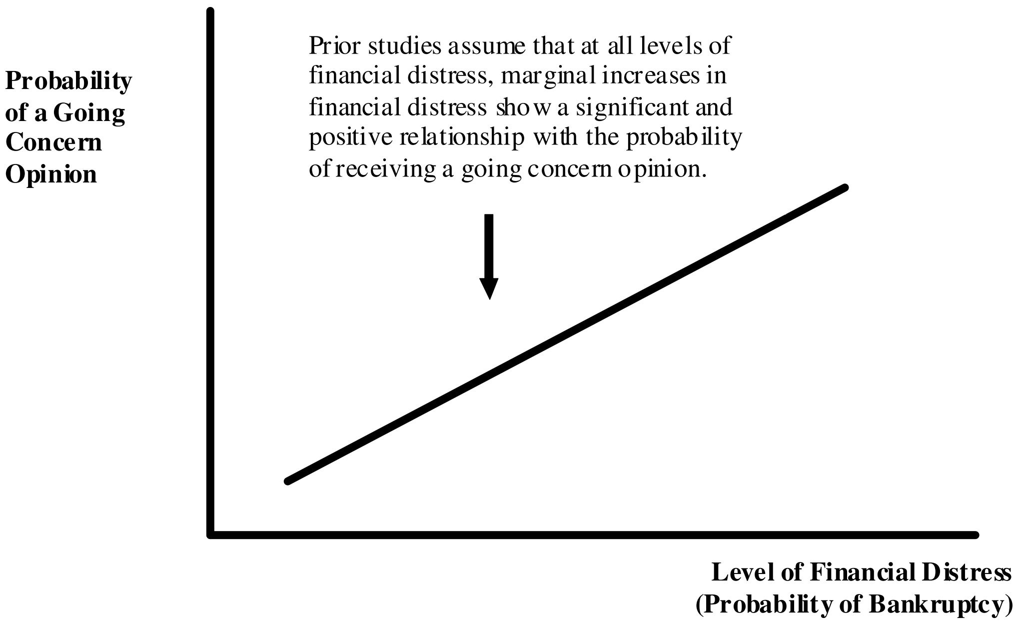

Figure 2

Hypothesis in Current Study:
Relationship Between the Level of Financial Distress and the Probability of Receiving a Going Concern Audit Opinion

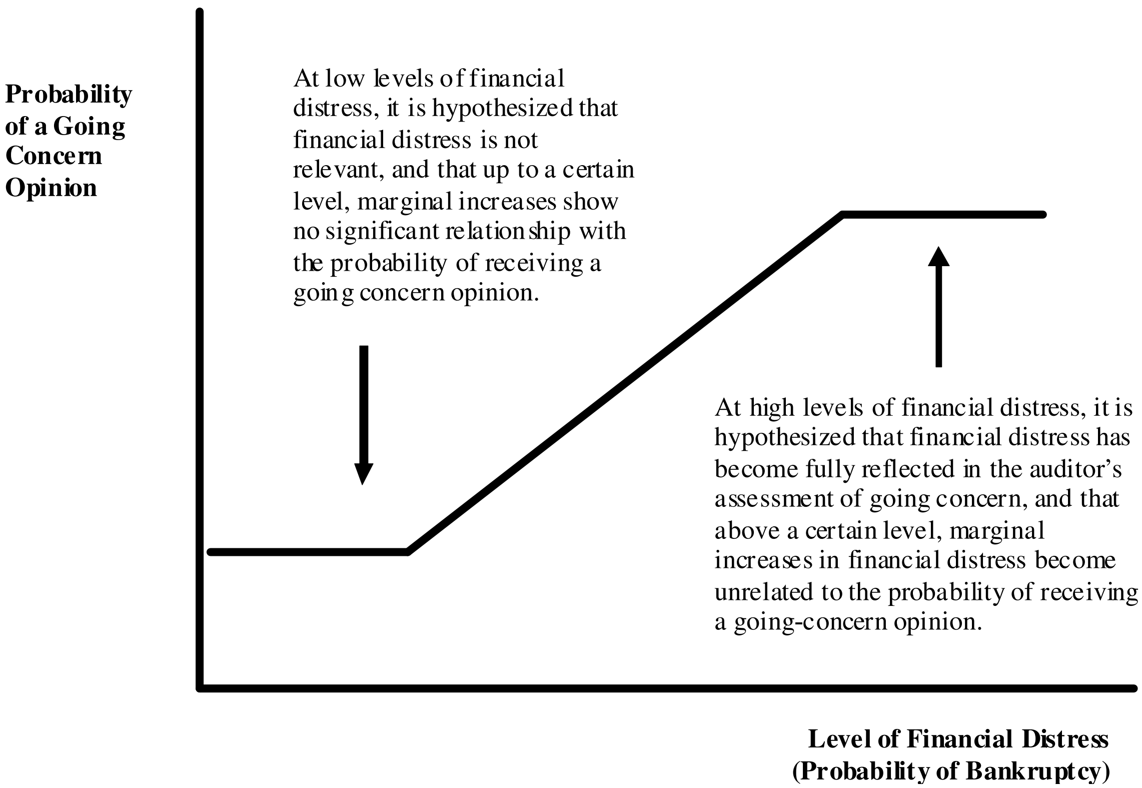

Table III Logistic Regression Results (Financial Distress Measured Using Altman's Z Score)

Model [1]: $GC = \beta_0 + \beta_1$ DISTRESS + β_2 LNSL + β_3 BLAG + β_4 RLAG + β_5 BIGN + β_6 DFLT + β_7 EXCH

	Logistic Results for Various Levels of Financial Distress [2]		
Variable	Category 1	Category 2	Category 3
Intercept	15.5631 (3.68) *	53.1311 (7.75) *	-.4756 (-.03)
DISTRESS	-5.7243 (-1.14)	-89.2689 (-6.59) *	24.69 (.82)
LNSL	-.3401 (-1.91)	-.1747 (-3.35) *	-.5813 (-3.68) *
BLAG	-.1264 (-2.17) *	-.2033 (-10.32) *	-.2501 (-4.39) *
RLAG	-.2713 (-2.14) *	.0589 (1.49)	.0522 (.76)
BIGN	-1.3015 (-2.04) *	-.3949 (-1.85)	.2609 (.49)
DFLT	.2971 (.76)	.3237 (1.23)	.2638 (.22)
EXCH	-.5702 (-.67)	-.0095 (-.05)	.0056 (.01)

1 Variables as defined in the body of this paper.

2 The DISTRESS variable in the regression model was Altman's Z score.
The logit model was run separately for each of the three categories of scores:
Category 1: Lower 15 percent of DISTRESS values
Category 2: Middle 70 percent of DISTRESS values
Category 3: Upper 15 percent of DISTRESS values

* Significant at the .05 level. Chi-square values in parentheses.

Table IV Logistic Regression Results (Financial Distress Measured Using Hopwood's (1994) Bankruptcy Probability Score)

Model [1]: $GC = \beta_0 + \beta_1$ DISTRESS $+ \beta_2$ LNSL $+ \beta_3$ BLAG $+ \beta_4$ RLAG $+ \beta_5$ BIGN $+ \beta_6$ DFLT $+ \beta_7$ EXCH

	Logistic Results for Various Levels of Financial Distress [2]		
Variable	Category 1	Category 2	Category 3
Intercept	7.7158 (3.13) *	6.4086 (4.01) *	4.5631 (1.32)
DISTRESS	.7474 (.19)	9.7482 (5.14) *	1.9859 (.87)
LNSL	-.2764 (-2.30) *	-.4146 (-7.36) *	-.0086 (-.07)
BLAG	-.2186 (-4.83) *	-.2074 (-10.18) *	-.0829 (-1.54)
RLAG	-.0024 (-.04)	.0745 (1.81)	-.2190 (-1.78)
BIGN	-.0735 (-.17)	-.3345 (-1.52)	-2.3487 (-3.00) *
DFLT	-.0332 (-.05)	.5002 (1.79)	.3427 (.89)
EXCH	-.3754 (-.93)	-.2370 (-1.20)	.6337 (.97)

1 Variables as defined in the body of this paper.

2 The DISTRESS variable in the regression model was Hopwood's (1994) Bankruptcy Probability Score. The logit model was run separately for each of the three categories of scores:
Category 1: Lower 15 percent of DISTRESS values
Category 2: Middle 70 percent of DISTRESS values
Category 3: Upper 15 percent of DISTRESS values

* Significant at the .05 level. Chi-square values in parentheses.

Table V Logistic Regression Results (Financial Distress Measured Using Zmijewski's (1984) Bankruptcy Probability Score)

Model [1]: $GC = \beta_0 + \beta_1$ DISTRESS + β_2 LNSL + β_3 BLAG + β_4 RLAG + β_5 BIGN + β_6 DFLT + β_7 EXCH

	Logistic Results for Various Levels of Financial Distress [2]		
Variable	Category 1	Category 2	Category 3
Intercept	3.0636 (.56)	2.7406 (1.36)	2.3762 (.58)
DISTRESS	19.3651 (1.38)	19.4330 (5.52) *	5.2965 (1.43)
LNSL	-.5339 (-4.33) *	-.4244 (-8.16) *	-.0791 (-.55)
BLAG	-.2197 (-4.02) *	-.2112 (-10.43) *	-.0875 (-1.78)
RLAG	.0044 (.05)	-.0018 (-.05)	.0199 (.08)
BIGN	.5639 (1.07)	-.4045 (-1.86)	-1.7733 (-2.30) *
DFLT	.3426 (.35)	.2478 (.90)	.2161 (.75)
EXCH	.3537 (.54)	.0206 (.11)	.0824 (.13)

1 Variables as defined in the body of this paper.

2 The DISTRESS variable in the regression model was Zmijewski's (1984) Bankruptcy Probability Score. The logit model was run separately for each of the three categories of scores:
Category 1: Lower 15 percent of DISTRESS values
Category 2: Middle 70 percent of DISTRESS values
Category 3: Upper 15 percent of DISTRESS values

* Significant at the .05 level. Chi-square values in parentheses.

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Asian FX Market Crisis: A Bayesian GARCH Models Approach

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Abstract

The aim of the paper is to study the principal GARCH models namely the GARCH(1, 1) and the student t-GARCH(1,1) used in financial time series, and to perform inference using a Bayesian approach. The paper concentrates on using four Financial Asian Foreign Exchange (FX) Market Risk high frequency opening daily rates. The Bayesian computational approach used for making inference about the model parameters is Markov Chain Monte Carlo (MCMC). The key development of the paper is the implementation of this Bayesian computational approach used with an objective to improve the performance of the Bayesian MCMC method.

I. Introduction

Amongst financial time series forecasting models, deterministic volatility models, specifically Autoregressive Conditional Heteroscedastic (or ARCH) type models is recognized as one of the important class and popular model. The ARCH model itself was originally proposed by Engle (1982). The original theory of the ARCH model is further expanded to many plausible well-defined empirical models. For example, Bollerslev (1986) extends ARCH to Generalized ARCH (GARCH) which hypothesizes that the conditional variance depends on its own past values, and past values of squared error terms. Amongst ARCH type models, GARCH (1, 1) model is recognized as one of the most important class as it has the ability to capture the commonly observed change in variance of the observed stock index or exchange rate over time, namely *Volatility*.

Volatility plays an important role in financial forecasting because it measures the amount of fluctuation in asset prices and the randomness which dramatic price changes frequently make. The advantage of modelling with volatility in finance theory is that it is a quantity that can be derived via the movement in price to capture its underlying magnitude, and used to identify the best way of predicting the true value of tomorrow's price in the trading market. It is subsequently used as a risk measure in many asset return models, options and other derivative security pricing models.

The goal of this paper is to introduce an ordinary GARCH (1, 1) and the student *t* GARCH (1, 1) models to obtain better estimates of the changing variance for the Asian financial price returns, which leads to forecasting the returns themselves at any given time point. To achieve such a goal, modelling and inference must be carried out efficiently with the available price returns. The Bayesian inference has become very attractive for GARCH models (Nakatsuma, 2000). The primary purpose of this paper is to apply the Bayesian approach for these univariate GARCH (1, 1) models in order to use for capturing the zero returns series.

II. The Asian FX Crisis Markets

Asian FX markets normally vary in terms of their banking systems, and most operate under government rules. The sizes of the banking systems however, are not comparable, and they differ considerably in terms of their commercial banks and financial companies. For example, the local commercial banking system in Hong Kong is about the same size as Singapore and Malaysia combined. Moreover if these three countries were added together, the size of the banking system would be similar to that of Taiwan. However, there is one factor that unites the FX markets of all Asian countries; they all compare their currency level against the US Dollar (USD). It is Dollar Zone dominant, even though they are in a global FX financial market, where there are other dominant currency trading players. Singapore, Japan, and Hong Kong have their own foreign exchange markets, and most of their currencies are traded in main centres abroad, beyond the control of the local authorities as highlighted by Gough (1998).

The Asian Crisis

On the 2 July 1997, the crisis started in Thailand, when speculators around the world attacked the Bank of Thailand by selling all their Thai Baht (THB) on the market; see Henderson (1998) for further discussion. The Asian financial panic caused the Philippine currency to collapse next, followed one-by-one by the other Asian currencies. This chain of events drew in the currencies of Malaysia, Indonesia, and South Korea. The attack lead to the crisis in the Asian currencies, and destroyed their stock markets, banking and financial institutions, manufacturing, and economic balances completely. Their currencies fell by over 40% against the US Dollar and their GDP growth rates became negative.

All three were compelled to turn to the rescue packages of the International Monetary Fund (IMF), as the only offer they had no choice but accept Delhaise (1998). However, the disease of the currency crisis did not spread to some others Asian countries with healthier economies such as China, and Taiwan. In addition, countries like Singapore, Hong Kong and Japan had their own foreign reserves. Therefore although, for example, Singapore had seen its currency soften, it did not have any significant foreign debt. With this in mind, we shall include these three currencies in our analysis.

The Asian Market Risk: FX Crisis Data

In our research, we have confined ourselves to the study of the FX markets of Thailand (THB), Singapore (SGD), Japan (JPY) and Hong Kong (HKD). The first two are referred to as the South East Asian countries. They belong to the ASEAN (Association of South East Asian Nations) organization, and are close trading partners. ASEAN was formed in 1967, originally with six countries (Malaysia, Indonesia, the Philippines and Brunei are the remaining four). The last two countries are often referred to the North East Asian countries.

The time period covered this particular FX data set chosen mainly includes the biggest crisis in Asian financial markets in 1997 .This means there are plenty of zero returns FX series. We obtained 4 daily sets of Asian FX data series against the US Dollar (USD). The data series obtained are from Olsen & Associates (www.oanda.com) with length, n =2300 for all currencies with daily rates, covering the crisis period from the 12 December 1996 to the 30 March 2003. The data crisis series have (kurtosis, zero returns values) of (94.33, 320) for THB, (17.82, 248) for SGD, (11.90, 88) for JPY, and (314.20, 516) for HKD. The latter had the highest zero-returns series. Each of our FX data series have locations (time points) where there appears to be systemic change; this indicates a nonstationarity in the overall process and that certain segments may need to be considered separately. For example, the data and returns plots of daily THB/ daily USD rates are displayed in Figure. 1. The dotted lines in this figure represent the location of the nonstationarity effect.

For any given series of historical prices $\{y_t\}$, $(t = 1,..,n)$ we define the daily percentage returns R_t as $R_t = 100 \text{ x } \log (y_t / y_{t-1})$. These returns are termed continuous compound or log returns. Note that for small changes in $\{y_t,\}$, $\log(y_t/y_{t-1})$ is approximately equal to the relative change $(y_t - y_{t-1}) / y_{t-1}$ We aim to model the variability in $\{y_t\}$, specifically its volatility or how the variance of $\{y_t\}$ changes through time. This quantity is extremely important when calculating the market risks; for example market risk can be measured in terms of the standard deviation of the returns.

III. Bayesian Inference

A general introduction to Bayesian inference is given in Bernardo and Smith (1994). A Bayesian model is a probability model that consists of a likelihood function and a prior distribution. In the

Bayesian calculation, the posterior distribution of θ given y is written in Equation (1) as

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)} = \ = \frac{p(y|\theta)p(\theta)}{\int p(y|\theta)p(\theta)d\theta}, \quad (1)$$

All inference procedures like moment calculation, estimation, and decision making are based on this posterior distribution. Inference in the Bayesian approach often requires advanced Bayesian computation, and here we focus on Markov Chain Monte Carlo (MCMC) sampling. MCMC techniques are now well established and widely used. The volume of discussion papers and books on the MCMC sampling is enormous. Amongst them are Bernardo and Smith (1994), Gilks *et al*, (1996), Gamerman (1997), and Roberts and Casella (1999) which review general references and the characteristics of the MCMC sampling. Other discussion papers highlighting the practical use of MCMC include Geyer (1992) and Gilks and Wild (1992). A general introduction and explanation of the MCMC approach is provided in Gilks *et al*. (1996).

The key aspect in the Bayesian inference setting is to define precisely the form of the one-step ahead conditional distribution so that the equilibrium distribution is required Bayesian posterior distribution. The MCMC methods will be the main inference technique implemented in this paper. Bernado and Smith (1994) provide further details of the basic Bayesian MCMC procedure. The two most commonly-used methods are the Gibbs sampler introduced by Geman (1984) and the Metropolis-Hasting (MH) originally developed by Metropolis (1953) and further generalized by Hastings (1970). These two samplers are simple to implement and are effective in practice when used for Bayesian inference.

IV. GARCH Models

The GARCH (1, 1) Model

In GARCH (1, 1) model, the parameters that need to be focussed on are α_1, β_1, and in particular ($\alpha_1 + \beta_1$) which is recognized by Kim (1998) as a persistence parameter. The GARCH (1, 1) process is defined as Equation (2):

$$\sigma_t^2 = \alpha_0 + \alpha_1 y_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (2)$$

with parameters $\alpha_0 \geq 0, \alpha_1 \geq 0, \beta_1 \geq 0$. When β_1=0, the above equation becomes ARCH (1) and so ARCH (1) model is said to be a special case of GARCH (1, 1) .The properties of the implied observable process in a straight forward fashion for the simplest GARCH (1, 1) Model and the GARCH (p, q) process can be found in Bollerslev (1986). Bollerslev (1992) suggested that GARCH (1, 1) is the simplest and very useful model. Engle (1993) notes further that GARCH (1, 1) is the most widely and successfully used model when estimating the volatility returns.

Being a simple model, it avoids the problems of over fitting and still has been found to have the main features present in more complex models. One of the main reasons that the GARCH (1, 1) model became heavily popular is that they have an ability to explain the stylized facts of volatility well. In financial time series, we observe certain stylized facts about volatility which are evident in price returns. These features, noted in Ghysels (1996) and Aydemir (1998), play a crucial role in model construction and selection. We attempt to use a model specification in which stylized features can be mimicked.

The Bayesian GARCH (1, 1) Model

With the GARCH (1, 1) model from equation (2) we consider the following priors for the GARCH parameters

$$\log \alpha_0 \sim N(0, \sigma^2_{\alpha_0}), p(\alpha_0) = \left(\frac{1}{2\pi\sigma^2_{\alpha_0}}\right)^{\frac{1}{2}} \alpha_0^{-1} exp\left(-\frac{(log\alpha_0)^2}{2\sigma^2_{\alpha_0}}\right), \quad (3)$$

$$\alpha_1, \beta_1 \sim Dirichlet(\gamma_1\gamma_2\gamma_3), \quad (4)$$

$$p(\alpha_1, \beta_1) = \frac{\Gamma(\gamma_1\gamma_2\gamma_3)}{\Gamma(\gamma_1)\Gamma(\gamma_2)\Gamma(\gamma_3)} {\alpha_1}^{\gamma_1 - 1} {\beta_1}^{\gamma_2 - 1} (1 - \alpha_1 - \beta_1)^{\gamma_s^{-1}}, \quad (5)$$

where we choose $\sigma^2_{\alpha_0} = 5$, $\gamma_1 = \gamma_2 = \gamma_3 = 1$. The *Dirichlet* prior is the most commonly used prior for parameters restricted to a simplex region and can be tailored to respect genuine prior beliefs; here the Uniform prior is used, but a prior model that favours large $(\alpha_1 + \beta_1)$ and near nonstationarity can also be specified. Considering the likelihood function of this model from full posterior distribution for the GARCH (1, 1) model can be written as in equation (6):

$$\begin{aligned} p(\alpha_0, \alpha_1, \beta_1 | Y) = & \prod_{t=1}^{n} \left(\frac{1}{2\sigma_t^2}\right)^{\frac{1}{2}} exp\left(-\frac{y_t^2}{\sigma_t^2}\right) \\ & \times \alpha_0^{-1} exp\left(-\frac{(log\alpha_0)^2}{2\sigma^2_{\alpha_n}}\right) \times \alpha_1^{\gamma_1 - 1} \beta_1^{\gamma_2 - 1} (1 - \alpha_1 - \beta_1)^{\gamma_s - 1} \\ & \propto exp\left\{-\frac{1}{2}\sum_{t=1}^{n} log\left(\sigma_t^2 + \frac{y_t^2}{\sigma_t^2}\right)\right\} \\ & \times \alpha_0^{-1} exp\left(-\frac{(log\alpha_0)^2}{2\sigma^2_{\alpha_n}}\right) \times \alpha_1^{\gamma_1 - 1} \beta_1^{\gamma_2 - 1} (1 - \alpha_1 - \beta_1)^{\gamma_s - 1} \end{aligned} \quad (6)$$

A similar Bayesian approach has been implemented by Nakatsuma (2000). However, a different prior for $(\alpha_1 + \beta_1)$ is used where he sets the prior for all parameters to be Normal. We found that such prior is not appropriate since $(\alpha_1 + \beta_1)$ are restricted to lie between zero and one, and for stationarity must also lie in the region $(\alpha_1 + \beta_1) < 1$. Further discussion can be found in Bauwens (1998), where the griddy-Gibbs sampler is used and a comparison is made between this sampler and the MH algorithm.

The Student t GARCH (1, 1) Model

The Student-*t* GARCH (1, 1) model can be formulated as

$$Y_t = \epsilon_t \sigma_t^2, \ \ \varepsilon_t \sim N(0, k\lambda_t), \quad (7)$$

$$\lambda_t \sim IGamma\left(\frac{v}{2}, \frac{v}{2}\right), \quad (8)$$

and for stationarity of GARCH(1, 1): $0 < \alpha_1 + \beta_1 < 1$. The parameters $\lambda_t, t = (1, \ldots, n)$ modify the model so that

$$(Y_t | \sigma_t^2) \sim St(0, k\sigma_t^2, v), \quad (9)$$

where v represents the degree of freedom and takes some positive value, and k is a constant term. For the conditional variance of y_t to be finite, we require $v > 2$. Again, choosing a constant term $k = (v-2)/v$ ensures that the conditional variance of y_t remains as σ_t^2, and setting each $\lambda_t = 1$ recovers the original GARCH(1,1) model of Equation (2). For finite kurtosis, we need to have $v > 4$.

Likelihood Function for the t-GARCH (1, 1) Model

The likelihood function for the t-GARCH (1, 1) of Equation 7 is given as

$$f(y_t|\alpha_0,\alpha_1,\beta_1,v,\lambda_t) = \prod_{t=1}^{n}\left(\frac{v}{2\pi(v-2)\lambda_t\sigma_t^2}\right)^{\frac{1}{2}} exp\left(-\frac{vy_t^2}{2(v-2)\lambda_t\sigma_t^2}\right), \quad (10)$$

$$\text{with } (\lambda_t|y_t,\sigma_t^2) \sim IGamma\left(\frac{v+1}{2},\frac{1}{2}\left[\frac{vy_t^2}{(v-2)\sigma_t^2}+v\right]\right), \quad (11)$$

As found by Bollerslev *et al*. (1994), the likelihood function for the (standardized) Student-*t* distribution denoted as z_t of GARCH (1, 1) can be written as (By rescaling the Student-*t* distribution of Y_t to standardized student *t* of $z_t = \frac{Y_t}{\sqrt{\frac{v}{v-2}}}$, $VaR[Y_t] = \frac{v}{v-2}$, and $VaR[Z_t] = 1$).

$$f(y_t|\alpha_0,\alpha_1,\beta_1,v) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\Gamma\left(\frac{1}{2}\right)\Gamma\left(\frac{v+1}{2}\right)}\left(\frac{1}{(v-2)\sigma_t^2}\right)^{\frac{1}{2}}\left(1+\frac{y_t^2}{(v-2)\sigma_t^2}\right)^{-(v+1)/2}, \quad (12)$$

for $v > 2$, where v allows for greater kurtosis and Γ denotes the Gamma Function. The log-likelihood function can be written as

$$logf(y_t|\alpha_0,\alpha_1,\beta_1,v) = logc(v) - \left(\frac{v+1}{2}\right)log\left(1+\frac{y_t^2}{(v-2)\sigma_t^2}\right) - \frac{1}{2}log(\sigma_t^2), \quad (13)$$

$$\text{where,} \qquad c(v) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\Gamma\left(\frac{v}{2}\right)\sqrt{(v-2)}} \quad , \quad (14)$$

for $4 < v < \infty$, the conditional kurtosis for the t – GARCH (1,1) model is 3 (v - 2) / (v - 4), which is greater than that of a normal. As $v \to \infty$, the Student density tends to a normal. All odd moments are zero. As before, where the kurtosis for the Student-t GARCH (1, 1) only exists if $v > 4$. Therefore, we will initially consider $v = 5$. In the GARCH model, we have essentially replaced *exp* (α_t) with σ_t^2 relative to the stochastic volatility equations of previous chapters.

The Bayesian t-GARCH (1, 1) Model

For the *t*-GARCH(1,1) model introduced above, if v is also to be included as an unknown parameter, we could use a discrete prior, where our chosen prior is $v \sim$ Pareto(2,γ); and if $\gamma = 1.6$ then the prior expectation is 5. Here we separate the model into two parts, (i) with $v = 5$, and (ii) with v unknown (where v is set to move freely).

V. MCMC Results

The purpose of estimating the GARCH parameters is to capture the behaviour of σ_t^2 in the future period of time. The GARCH parameters are $\alpha_0 \geq 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$. For this MCMC algorithm, the three parameters α_0, α_1, β_1 are recorded at every 500 run until it reached 2,500,000 thus the exact total number of run is 5000. Since α_0 is a constant term we shall focus on the estimation of α_1, β_1, and ($\alpha_1 + \beta_1$). The convergence and histogram plots and the posterior statistics output are analysed.

Convergence and Histogram Plots

For GARCH (1, 1), the trace and histogram plots of JPY/USD are displayed in Figure 2. Similarly for the *t*-GARCH (1, 1) with $v = 5$, plots of SGD/USD are displayed in Figure 3 and with v unknown, plots of HKD/USD are displayed in Figure 4. From the trace and histogram plots, all parameters appear to have converged. These empirical results are also true for the other data series; we conclude that the sample sizes are adequate to represent the posterior distributions.

Analysis of Posterior Output

The posterior statistics for each data series that summaries the three parameters in the GARCH (1, 1) and *t*-GARCH (1, 1) with v = 5 and v = unknown are presented in Tables 1, 2, and 3 respectively. In Table 1, the THB and JPY estimate the values of (α_1+β_1) to be significantly close to one; this is frequently occurs in practice. To explain the stability and persistence of GARCH (p, q) model, the sum of the (α_1+β_1) needs to be examined, as it explains the stationarity and persistence in GARCH (1, 1) volatility. In addition, the estimated values of α_1 are close to one and β_1 are close to zero. Thus there exists considerable persistence in volatility, moving towards nonstationarity.

In Table 2, the estimated values are shown to be very close to those obtained from Table 1. This evidence confirms that more persistence parameters in GARCH (1, 1) are closer to non-stationarity than those in the *t*-GARCH (1, 1) model. There is less persistence for these FX series than indicated in the GARCH (1, 1). All series produce values of (α_1+β_1) to be close to 1, with the highest value of 0.9924 for the THB indicating significant persistence in volatility. When v is unknown, the modal values of v are also displayed in the last column of Table 3. The posterior median and the modal values of v for JPY are approximately equal to 8.5. For HKD, the posterior median and the modal values of v are approximately equal to 5; which is found to be the lowest number when compared with other currencies. This result indicates that setting v to be 5 in the first *t*-GARCH (1, 1) model is an appropriate choice in particular to the worse crisis FX data with majority of zero returns series.

VI. Conclusion

The Bayesian approach used for the estimation of the GARCH (1, 1) and the *t*-GARCH (1, 1) models is found to be effective with our Asian FX series. The Dirichlet prior chosen for α_1, β_1 is an appropriate prior to use for such this model as it respects the constraints on the model parameters. For the GARCH (1, 1) model, the posterior median values of (α_1+β_1) are estimated to be very close to 1 for all series. The kurtosis values obtained suggest that a heavy-tail model distribution is required for all series. This finding is important for the arrival of the *t*-GARCH (1, 1) model. When comparing the two outputs using the same MCMC sampling scheme for the GARCH models, there is clear evidence that the persistence parameters (α_1+β_1) are close to 1, and thus are closer to non-stationarity in the GARCH(1,1) model than those in the *t*-GARCH(1, 1) model. This means that the distribution of these FX series when fitted with the *t*-GARCH (1, 1) model are found to be relatively close to normal thus a heavy-tail model distribution is required. In v is unknown, all data series apart from the HKD had the degree of freedom, v to be around 6 to 7. This currency is known to have the most zero returns out of all currencies. We conclude that each governmental policy, and the reaction of each nation, dictated the trends in the exchange rate series. From the crisis period until today, some currencies have remained compromised in value; for example, the THB still remains at 30-40/USD, which is about 40% lower compared to the level before the crisis. A currency like HKD still remained at its own rate level around 7.8/USD until now.

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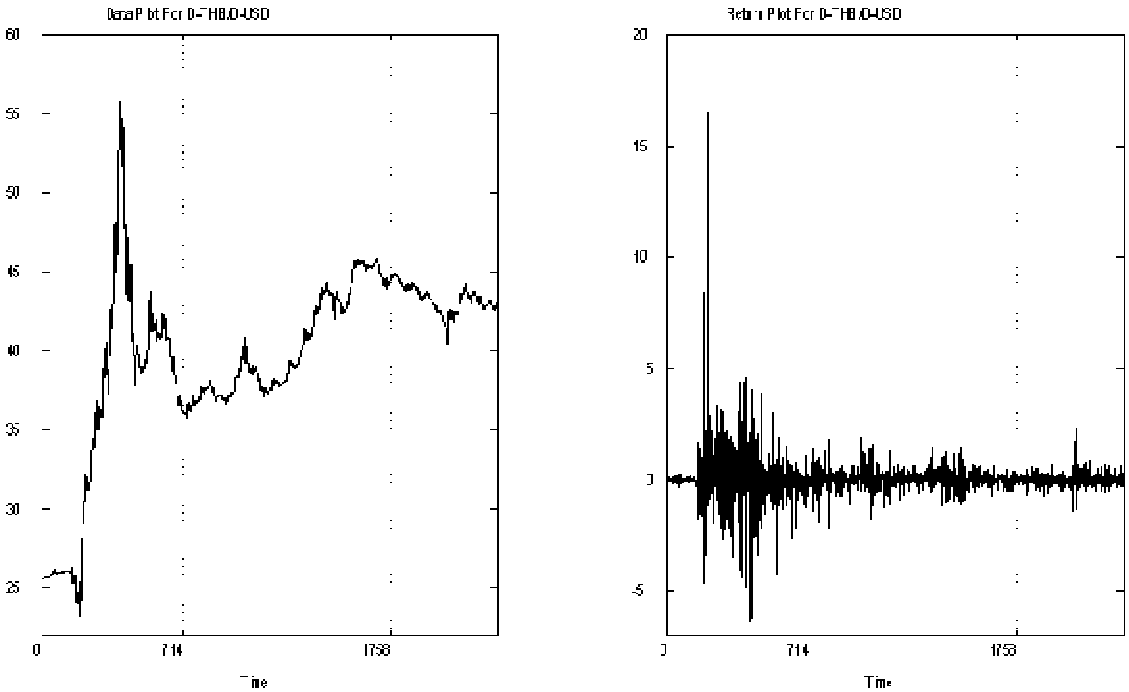

Figure 1: Plots of data and returns of daily THB /USD series.

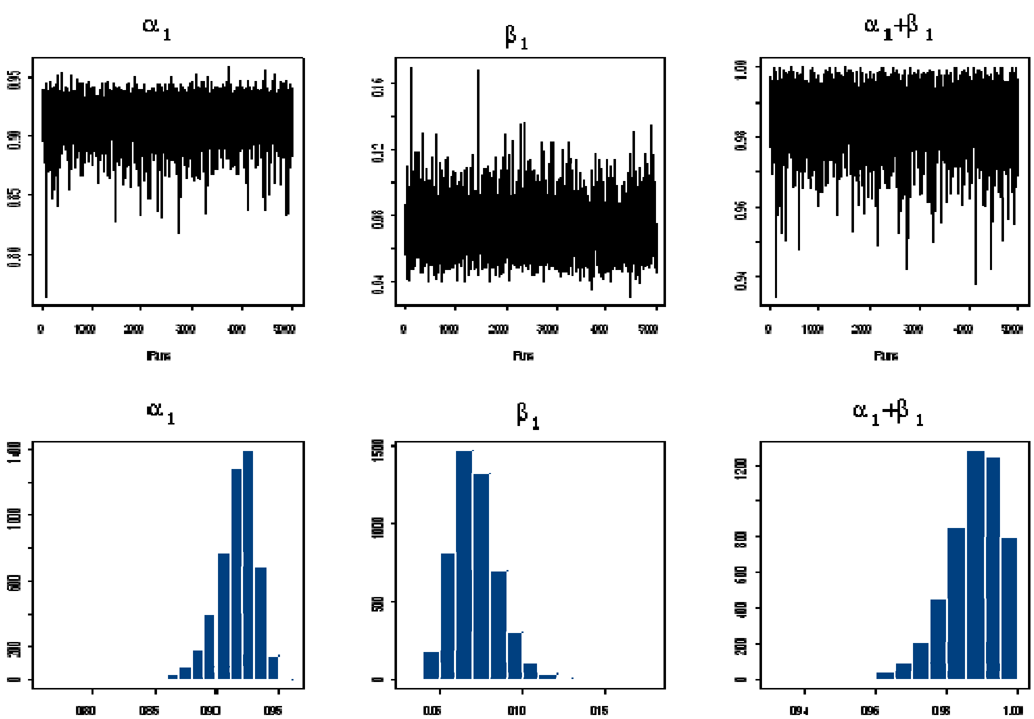

Figure 2: Plots of Bayesian GARCH (1, 1) model for $\alpha_1, \beta_1, \alpha_1 + \beta_1$ using JPY/USD

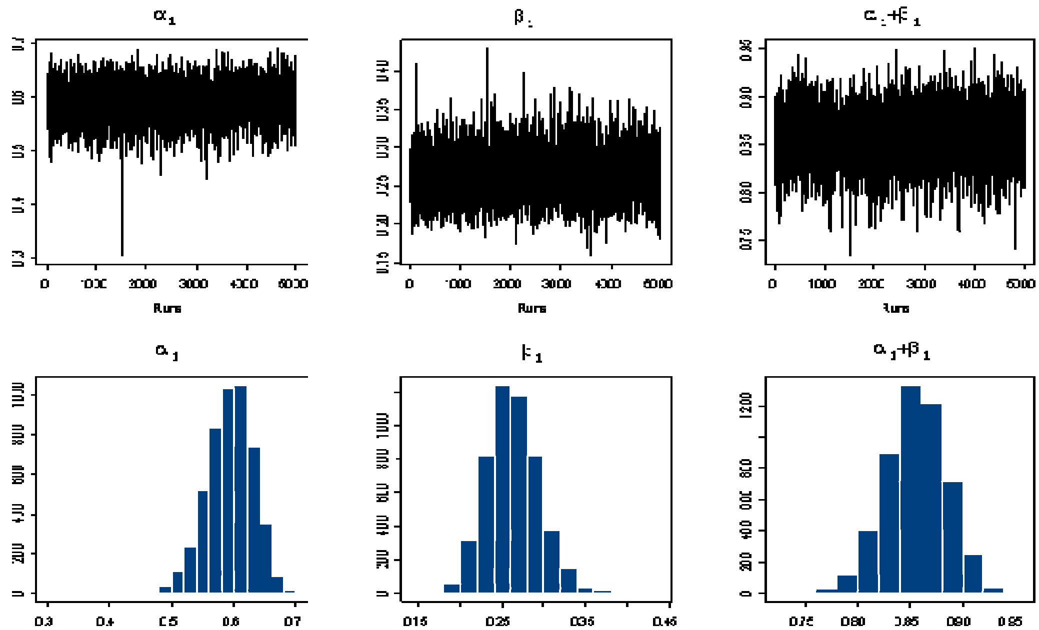

Figure 3: Plots of Bayesian *t*-GARCH (1, 1) model with v =5 for $\alpha_1, \beta_1, \alpha_1 + \beta_1$ using SGD/USD

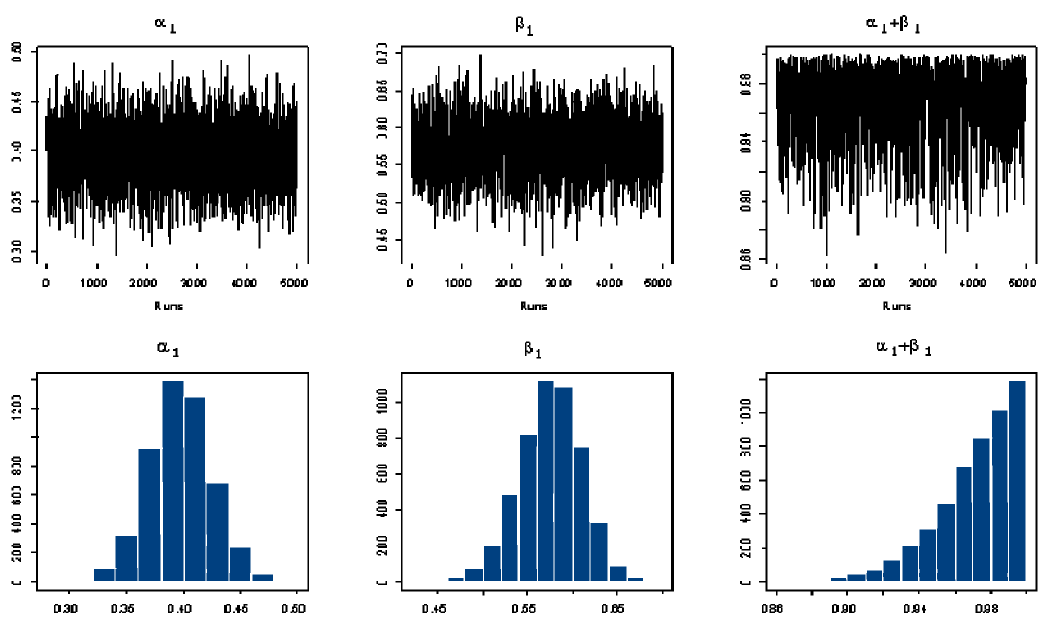

Figure 4: Plots of Bayesian *t*-GARCH (1, 1) model with v unknown for $\alpha_1, \beta_1, \alpha_1 + \beta_1$ using HKD/USD

Table 1. Posterior Statistical GARCH (1, 1) output

GARCH (1, 1)	α_1 Mean, Median, Std	β_1 Mean, Median, Std	$\alpha_1 + \beta_1$ Mean, Median, Std
THB	0.9036, 0.9039, 0.0091	0.0961, 0.0957, 0.0091	0.9997, 0.9998, 0.0004
SGD	0.0347, 0.0199, 0.0409	0.6248, 0.6403, 0.2144	0.6594, 0.6743, 0.2097
JPY	0.9159, 0.9181, 0.0160	0.0714, 0.0701, 0.0138	0.9872, 0.9883, 0.0079
HKD	0.0355, 0.0204, 0.0421	0.5823, 0.5804, 0.2208	0.6177, 0.6147, 0.2166

Table 2. Posterior Statistical *t*-GARCH (1, 1) output with $v = 5$

t-GARCH (1, 1) v = 5	α_1 Mean, Median, Std	β_1 Mean, Median, Std	$\alpha_1 + \beta_1$ Mean, Median, Std
THB	0.8672, 0.8677, 0.0148	0.1252, 0.1247, 0.0157	0.9924, 0.9924, 0.0048
SGD	0.5928, 0.5948, 0.0361	0.2628, 0.2612, 0.0310	0.8556, 0.8561, 0.0289
JPY	0.9507, 0.9521, 0.0107	0.0250, 0.0244, 0.0057	0.9757, 0.9769, 0.0072
HKD	0.3955, 0.3947, 0.0275	0.5754, 0.5776, 0.0347	0.9709, 0.9760, 0.0224

Table 3. Posterior Statistical *t*-GARCH (1, 1) output with v unknown

t-GARCH (1, 1)	α_1 Mean, Median, Std	β_1 Mean, Median, Std	$\alpha_1 + \beta_1$ Mean, Median, Std	V (modal) Mean, Median, Std
THB	0.8747, 0.8740, 0.0137	0.1157, 0.116245, 0.0147	0.9903, 0.9904, 0.0051	6.8834, 6.8834, 0.3640
SGD	0.6025, 0.6040, 0.0337	0.2490, 0.2472, 0.0285	0.8515, 0.8519, 0.0265	6.9735, 6.9735, 0.3619
JPY	0.9479, 0.9492, 0.0113	0.0239, 0.0234, 0.0053	0.9718, 0.9729, 0.0077	8.3251, 8.3251, 0.5570
HKD	0.3968, 0.3970, 0.0276	0.5750, 0.5761, 0.0348	0.9718, 0.9766, 0.0224	5.0460, 5.0460, 0.1667

Chaos Effect of Rare Earth Elements: An Artificial Neural Network Analysis

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Abstract

This study examines the chaos phenomenon of rare earth elements (REEs) and determines the more accurate forecast method for the prediction of REE prices. For the detection of chaotic behavior, this paper applied three different approaches, namely, the Brock Dechert Scheinkman test, the rescaled range analysis, and the correlation dimension analysis. For the prediction of REE prices, this research utilized two Artificial Neural Networks, namely, the Back Propagation Network (BPN) and the Time Delay Recurrent Neural Network (TDRNN), with determining factors such as the Broad Index, Baltic Dry Index, Commodity Research Bureau Futures Price Index, PHLX Semiconductor Sector index, NASDAQ Computer Index, and the London Interbank Offered Rate. This simulation not only found evidence of chaos in REE prices, but also discovered that employing TDRNN in REE prices has a better forecasting performance than employing BPN. Therefore, the associated REE inputs were determined to be effective indicators in REE forecasting.

Keywords: Rare Earth Elements Price Prediction; Chaos Effect; Artificial Neural Network.

I. Introduction

Rare earth elements (REEs), a group of 17 naturally occurring metallic elements including scandium, yttrium, and a group of 15 lanthanides, have recently received considerable attention from investors, traders, and policy makers because of the increase in their prices and usage in the field of green technology. Major REE applications include hybrid automobiles, plug-in electric automobiles, large wind turbines, computer hard drives, military weapons, and metal alloys. According to the United States Geological Survey (USGS), the demand for REEs was close to zero during the 1950s. However, after more than 30 years, approximately 20,000 tons REEs were utilized in 1984, approximately 140,000 tons in 2009, and approximately 160,000 tons in 2010.

China continues to be the world's largest producer of REEs. The country controls 97% of REE production. Aside from REE exportation, China is a dominant producer of lucrative products such as wind turbines, consumer electronics, and batteries for hybrid electric vehicles, among others. When China reduced the export of REEs by more than 70% in October 2010, the operation of manufacturers in Japan, Europe, the United States, and other importers was greatly disrupted.

Batten et al. (2010) investigated the macroeconomic factors (business cycle, monetary environment, and financial market sentiment) that affect the monthly price and volatility of four precious metals. The block exogeneity test results showed that monetary and financial variables are important factors in determining precious metal price movements and in forecasting precious metal volatilities. Their study also suggested that variables such as inflation, interest rate, and increase in money supply are more likely to affect the gold market. On the other hand, the return volatility on the S&P 500 and World S&P 500 were found to affect platinum and palladium markets.

In light of metal price forecasting, Bernard et al. (2006) applied mean square forecast error and non-parametric prediction error statistics and focused on the forecast performance of model appraisal in aluminum prices. Chen (2010) examined the volatility of the price movements of 21 metals from 1900 to 2007, a period which included the Great Depression of the 1930s, World War I, and World War II. He found that approximately 34% of price volatility can be attributed to global macroeconomic factors over the period 1972 to 2007.

Market movements apparently result from psychological factors such as collective opinions or emotions of fear and greed that make markets behave in an unpredictable, chaotic manner. Chaos

and its application in forecasting have been extensively discussed in the financial market. Peters (1996) noted two important features of chaotic behavior: (1) the existence of fractal dimension and (2) the sensitive dependence on initial conditions, commonly known as the butterfly effect.
Chaotic series differs from linear models that cannot capture data irregularities (Kohzadi et al, 1996). Chaotic systems are generally nonlinear response systems that have erratic behavior and discontinuities that affect the amplification of events. LeBaron (1994) argued that an extremely wide gap may exist between nonlinear forecasting and the actual identification of chaotic dynamics in financial markets. Dynamic chaotic systems in economics and finance were utilized by some economists and financial researchers (Benhabib and Nishimura, 1979; Grandmont, 1988; Day, 1992; Wolff, 1992; Bayley, 1998; Guegan and Leroux, 2007). Their studies suggest that the character of noise in real data sets is a distraction in the use of the chaos theory.
An artificial neural network (ANN) is a nonlinear statistical data processing technique that is associated with an input stream of information that is used to obtain an output stream of data. ANNs provide an alternative tool for both researches and practitioners. ANNs can detect the underlying functional relationships within a set of data and can perform tasks such as pattern recognition, classification, evaluation, modeling, prediction, and control (Anderson and Rosenfeld, 1988; Hecht-Nielsen, 1990; Hertz et al., 1991; Hiemstra and Jones, 1994). In particular, Refenes (1995) noted that ANNs have powerful pattern recognition properties and can outperform contemporary modeling techniques in numerous applications.
This study primarily aims to forecast the price of 17 rare earth elements by employing potential forecasting models. The exploration of price behavior behind the REEs provides investors with valuable information for comparisons of the accuracy of networks. The results show that the chaos effect exists in REE prices and suggest that the use of the Time Delay Recurrent Neural Network (TDRNN) in REE price data is more effective and yields better performance than employing the Back Propagation Network (BPN). Therefore, REE associated inputs as well as the Broad Index, Baltic Dry Index (BDI), Commodity Research Bureau Futures Price (CRB) Index, PHLX Semiconductor Sector index, NASDAQ Computer Index, and The London Interbank Offered Rate (LIBOR) would be good indicators for REE forecasting.
This paper is organized as follows: Section 2 describes the data and methodology. Section 3 presents the empirical results. Finally, Section 4 concludes.

II. Data

This study uses the historical prices of rare earth elements. The data collection period is from April 2001 to June 2010. Nine REE datasets were collected from the Asian Metal Web site. Asian Metal is a global information company founded in 2000. This company is a market leader that has produced recognized brands in the metal and steel research and consulting industry. The Asian Metal team serves over 100,000 companies from 200 countries worldwide. Rare earth metals have been used in modern high technologies and are crucial to green energy, lifestyle, and defense technology because of their rarity and high unit value. The appendix clarifies the applications of REEs.
The input variables that were used in this study including the NASDAQ Computer Index, the PHLX Semiconductor Sector, the Commodity Research Bureau Futures Price (CRB) Index, the Broad Index, the LIBOR Index, and the Baltic Dry Index will be detailed below.

1. NASDAQ Computer Index (Symbol: IXCO)

The NASDAQ Computer Index (symbol: IXCO) includes NASDAQ-listed companies that are classified according to the FTSE[10] Global Classification System as Computer Hardware, Semiconductors, and Software as well as Computer Services. The index includes 414 firms that manufacture and distribute computers associated with electronic data processing, electronic data processing equipment and accessories, semiconductor capital equipment, and wafers and chips; providers of computer and IT consultancy services, Internet access, Internet software and online services; as well as producers and distributors of computer software[11].

2. PHLX Semiconductor Sector index (SOXX)

The PHLX Semiconductor Sector Index (SOXX) is a price-weighted Philadelphia Stock Exchange index comprising companies that are primarily involved in the design, distribution, manufacture, and sale of semiconductors. SOXX is a price-weighted index; companies with higher stock prices have greater influence on the index.[12] In addition, SOXX is a closely watched index for "chip" stocks. Rare earth materials are used in several applications in semiconductor manufacturing.

3. CRB index

The CRB index of commodity prices, known as the most authoritative international commodity price index, reflects the consolidated performance of the world market. The CRB index is updated every 15 seconds; the initial production stage reflects the price level and trend of the general characteristics of commodity price movements. The product category also includes precious metals.

4. BDI

The BDI, one of the purest leading indicators of economic activity, measures the demand to move raw materials and precursors to production as well as the supply of ships available to move the cargo[13]. This measure of freight shipping costs has often been used as an early economic indicator. Given the global nature of shipping, this index may present a broad take on global economic health despite being a less reliable indicator of any specific nation's economy. Rare earth metal price fluctuations are primarily affected by supply and demand, environmental legislation, and economic factors, especially inflation and energy costs. Higher inflation and energy costs increase operating costs throughout the mining industry, whereas higher operating costs increase rare earth metal prices (USGS, 1999).

5. LIBOR

LIBOR interest rates, which are generally considered to be useful information for forecasting, can be used as inputs (Viceira, 2007, Estrella and Mishkin, 1998). LIBOR is often used as a rate of reference for the pound sterling and for other major currencies. Pacelli et al. (2011) used the LIBOR index as an input parameter for ANN forecasting.

6. Trade Weighted Exchange Index: Broad (TWEXB)

The Trade Weighted US dollar Index, also known as the Broad Index, is a measure of the value of the US Dollar relative to other world currencies. To reflect the strength of the dollar relative to

[10] The Financial Times Stock Exchange 100 stock index, a market cap weighted index of stocks traded on the London Stock Exchange.

[11] http://www.nasdaq.com/newsroom/presskit/reports/NFP_Fact_Sheet_03.pdf .

[12] http://www.marketvolume.com/indexes_exchanges/sem.asp.

[13] "Baltic dry index flashes warning lights for emerging markets". Market commentary, 3, September 2009. Source: http://www.nzfunds.co.nz/docs/Baltic%20dry%20index.pdf.

other world currencies accurately, the Federal Reserve created the Trade Weighted US Dollar Index, which includes a larger collection of currencies than the US Dollar Index. The index weights, which change over time, are derived from US export shares and from US and foreign import shares. The changes in the US dollar exchange rates, economic situations, and political events affect metal and mineral supply and demand[14]. Labys et al. (1999) showed that exchange rate factors affect metal price volatility. The data set of TWEXB is extracted from the Federal Reserve Bank Reports.

III. Methodology

This study tested how the underlying time series data of REEs behave during chaos and then employed three different approaches. In addition, this study further utilized a popular forecasting technique, ANNs, specifically BPNs and TDNNs.

1. Chaos Effect

(1) BDS test

Grassberger and Procaccia (1983) identified chaotic behavior in time series data. Formally, let { x_t } be a scalar time series of size T that is generated randomly according to a density function f to form m-dimensional vectors, called m-histories, $x^m_t = (x_t, x_{t+1},..., x_{t+m-1})$. The sample correlation integral (or correlation sum) at embedding dimension m is computed as

$$C_{m,t}(\varepsilon) = 2\sum_{t=1}^{T_{m-1}}\sum_{t=1}^{T_m} I_\varepsilon\left(x_t^m, x_u^m\right)/\left(T_m\left(T_m - 1\right)\right), \tag{1}$$

where $Tm=T–m+1$, and $I_\varepsilon\left(x_t^m, x_s^m\right)$ is an indicator function of the event

$$\left\|x_t^m - x_s^m\right\| = \max_{i=0.1..m-1} \left|x_{t+i} - x_{s+i}\right| \le \varepsilon.$$

Further, the correlation integral at embedding dimension m is defined as

$$C_m(\varepsilon) = \lim_{T\to\infty} C_{m,T}(\varepsilon)\cdot \tag{2}$$

The correlation dimension test is ineffective when applied in relatively short data sets (several thousand observations or less), noisy data, or non-stationary series. These problems result in the development of the behavior data systems (BDS) test (Brock et al., 1996), which is derived from the Grassberger–Procaccia method.

$$BDS_{m.T}(\varepsilon) = T^{\frac{1}{2}}\left[C_{m.T}(\varepsilon) - C_{1.T}(\varepsilon)\right]/\sigma_{m.T}(\varepsilon). \tag{3}$$

Based on a limiting standard normal distribution, σm,T(ε) is an estimate of the asymptotic standard error of [C*m,T* (ε) - C*1,T* (ε)n].

(2) Rescaled Range Analysis (R / S) Analysis

Hurst (1951) developed a statistical method to measure the existence of the long-term memory phenomenon in a time series. The calculation process is as follows:

1). A time series of data segments is created.

Assume the time series (x_t) of all observed values u can be divided into n-intervals.

2). The cumulative sub-interval of the average bias is calculated.

Average

$$M_n = \frac{1}{n}\sum_{t=1}^{n}(Xt), \tag{4}$$

[14] Rare Earth Metals Inc, (2011). Source: http://www.rareearthmetals.ca/upload/documents/racorp_apr11.pdf.

$$\text{Cumulative errors: } X_{t,N} = \sum_{u=1}^{t}(X_t - M_n), \tag{5}$$

a) The value of the whole range of R is calculated.

Cumulative errors from each interval of the full range

$$R_N = \max(X_{t,N}) - \min(X_{t,N}),\ 1 \le j \le n. \tag{6}$$

b) The Hurst exponent is calculated.

The relationship of Hurst's law is shown as follows:

R / S = (an) H,

where R/S stands for the rescaled range, *n* for all the observations, *a* for the fixed constant, H for the Hurst exponent, and S for the standard deviation. The formula below takes the natural logarithm for the H values.

$$\ln\left(\frac{R(n)}{S(n)}\right) = H\ln(an),\ \text{H} = \ln(\text{R / S}) / \ln(\text{an}). \tag{7}$$

If H is equal to 0.5, the time series increments have 0 related coefficients in between, which means that the increments are not correlated; If $0 \le H < 0.5$, the time series increments have a related coefficient smaller than 0, which means that the increments are negatively correlated; If $0.5 < H < 1$, the time series increments have a related coefficient bigger than 0, which means that the increments are positively correlated.

The time series continuity or the memory effect is an early post-change data value. The R/S analysis combined with the Hurst exponent of time series parameters can be used to show a long non-periodic cycle when examining the long memory of indexes.

(3) Correlation Dimension Analysis

Grassberger and Procaccia (1983) measured the distance among group values, which were smaller than a certain degree of correlation dimension analysis. Dimension is related to freedom in the measurement system that calculates the value of discrimination. To measure the degree of complexity, the correlation dimension analysis determines whether the data indicates a chaotic phenomenon.

In the chaotic process, the correlation dimension is a non-integer value that converges to the saturation point with the continued increase in random processes (Moshiri and Foroutan, 2006).

In this study, the calculation of the correlation dimension algorithm can be achieved through the following steps:

1). The autocorrelation and conditional heteroskedasticity in the residual analysis is removed.

2). The embedded dimension n is defined. The embedding dimension value should not be greater than the length of the original sequence and should not be less than 1.

1-history: $x_t^1 = x_t$,

2-history: $x_t^2 = (x_{t-1},\ \ x_t)$,

n-history; $x_t^n = (x_{t-n+1},\ldots,x_t)$.

An n-history is a point in n-dimensional space; n is called “embedded dimensions.”

3). The correlation integral is calculated. Grassberger and Procaccia (1983) defined the integration process as

$$C_n(\varepsilon) = \lim_{T\to\infty} \#\left\{(t,s), 0 < t,s, < T : \left\|x_t^n - x_u^n\right\| < \varepsilon\right\} / T^2, \tag{8}$$

where # denotes the set of all points in space and the sum of the minimum and maximum value. The measurement of (x_u^n , x_t^n) distance indicates

$$\max_{i=0,\ldots,n-1}\left\{\left|x_{u-i}-x_{t-i}\right|\right\}<\varepsilon. \quad (9)$$

4). The minimum value of ε, which represents the slope for the calculation of demand, $\|\ \|$ is computed. The slope for the calculation of demand is as follows:

$$v_n=\lim_{\varepsilon\to 0}\log C_n(\varepsilon)/\log\varepsilon. \quad (10)$$

If the correlation dimension (v_n) does not vary with the increase in n, the data is consistent with the chaotic phenomena. However, if the increased embedding dimension and the correlation dimension have no convergence, the series does not have a fractal structure and is inconsistent with a chaotic system.

2. ANN Model Design

ANN section simulation builds upon the ideas of Kaastra and Boyd (1996), who organized the steps in the design of a neural network forecasting model. Data pre-processing is important in obtaining good prediction performance. Given the chaotic nature of data, data normalization (Kaastra and Boyd, 1995; Shanker et al., 1996; Bódis, 2004) is required because the values of a time series can vary between wide ranges within a short period of time; this condition makes the prediction difficult. To avoid this problem, all the raw data in the input series must be scaled between 0 and 1.

ANNs require the division of data and the creation of training samples. Training samples are used in the ANN model, whereas the test sample is the remainder of the data adopted for the evaluation of the forecasting capability of the model. Nam and Schaefer (1995), who tested the impact of different training samples, concluded that as the training sample size increases, ANN forecaster performance improves. According to empirical evidence (Chakraborty et al., 1992; Gorr et al., 1994), 90:10 portions were employed in this study.

Layers of nodes comprise the ANN structure. In designing an ANN model, the number of input nodes is initially determined, followed by the number of hidden layers and the hidden nodes as well as the number of output nodes (Zhang et al., 1998; Maditinos and Chatzoglou, 2004). Kaastra and Boyd (1995) noted that one or two hidden layers usually have efficient performance in empirical studies; thus, they recommended that the design process could start with one or two hidden layers. Moreover, Bódis (2004) argued that two hidden layers have better learning capability for any linear or nonlinear problem. This paper tested one and two hidden layers for each of dependent variable. Kaastra and Boyd (1995) recommended the testing of as many randomly starting weights as computational constraints allow. This study utilized 1,000, 10,000, and 100,000 iterations in choosing the best performance for each index.

A transfer function determines the relationship between the inputs and outputs of a node and a network. The activation function generally introduces a degree of nonlinearity that is valuable for most ANN applications. This work utilized the sigmoid function, the most efficient function available, as the activation function (Chakraborty et al.,1992; Tang et al., 1991, 1993; Srinivasan et al., 1994; Zhang,1994; Nam et al., 1995). The sigmoid (logistic) function can be expressed as

F(x)=(1+exp(-x))-1. (11)

Zhang et al. (1998) noted that neural network software programs provide appropriate default values for the learning rate. In this work, training was initiated with a higher learning rate, such as 0.7; the rate was slowly decreased as the training proceeded.

1) Back propagation networks

Refenes et al. (1997) explained that BPNs are more efficient for nonlinear data. Minsky and Papert (1969) initially formulated a two-layer feed-forward network that can overcome numerous restrictions, but did not solve the problem of weight adjustment from the input to the hidden layer.

The output of the BPN depends on the sigmoid transfer function and can be shown as

$$f(x) = \frac{1}{1+e^{-x}}, \tag{12}$$

where *f (x)=x* is the input layer. The expected output is within the range $0 \le y \le 1$ if the sigmoid function is used.

2) TDRNN

The TDRNN is an extensive neural model from the traditional recurrent neural network. TDRNN has the advantages of adaptive time delays and recurrences. These adaptive time delays help the network in the selection of useful information with time lags for temporal correlations and predictions in the input sequence. On the other hand, recurrences enhance learning capability and integrate the temporal context information of sequences for the network. Recurrences contain shorter training times for convergence and have efficient performance in identifying the temporal location.

According to Kim (1998), the TDRNN equation is

$$net_{j,h}(t_n) = \sum_{i \in N_{h-1}} \sum_{k=1}^{K_{ji,h-1}} \omega_{jik,h-1} \cdot a_{i,h-1}(t_n - \tau_{jik,h-1}), \tag{13}$$

where $a_{i,h-1}(t_n - \tau_{jik,h-1})$ is the activation level of unit i on layer h- 1 at time , N_{h-1} denotes the set of nodes of layer h-1, and represents the total number of connections to node j of layer h from node i of layer h-1. The output of node j is governed by a non-decreasing differential function f of the net input.

$$a_{j,h}(t_n) = \begin{cases} f_{j,h}(net_{j,h}(t_n)) & if\ h \ge 2, \\ a_{j,0}(t_n) & if\ h = 1, \end{cases} \tag{14}$$

$$\text{where } f_{j,h}(net) = \frac{\beta_{j,h}}{1+e^{-\alpha_{j,h} \cdot net}} - \gamma_{j,h}, \tag{15}$$

and denotes the j-th channel of the input signal at time t_n and $\alpha_{j,h}$, whereas $\beta_{j,h}$ and $\gamma_{j,h}$ are real numbers. $\gamma_{j,h}$ and $\beta_{j,h}$ - $\gamma_{j,h}$ are the upper and lower sigmoidal function bounds, respectively. The steepness of $f_{j,h}(net)$ can be expressed by $f'_{j,h}(0)$ is $(\alpha_{j,h} * \beta_{j,h})/4$.

3) Criteria for performance measures

A key aspect of forecasting is accurate measurement, which is often defined in terms of forecasting error. This error denotes the difference between the actual (desired) and the predicted values (Zhang et al., 1998).

Mean absolute error (MAE) measures the size of the forecast error; it is the average absolute prediction error. A lower MAE value or one that is closer to the actual value expresses better predictive capability. MSE is the most frequently used accuracy measurement technique in related literature (Kang, 1991; Chakraborty et al., 1992; Kohzadi et al., 1996; Bódis, 2004; Ali, 2009). Root mean absolute error (RMSE) determines the absolute fit of the model to the data in terms of the closeness of the observed data points to the predicted values. Lower RMSE values indicate a better fit. Ginzburg and Horn (1994) concluded that RMSE is the most important criterion if a model primarily aims to predict.

IV. Empirical Results

Metal price series and futures prices mostly have unit roots with nonstationary series (Labys et al., 1999; Moore and Cullen, 1995; Beck, 2001). The REE series were filtered by using an autoregressive integrated moving average (ARIMA) model to remove linear dependence and by using autoregressive conditional heteroskedasticity (ARCH)-type models to eliminate conditional heteroskedasticity. This study also applied BDS test, R/S analysis, as well as correlation dimension test in residuals from linear model filters.

1. Unit Root Test

Table 1 shows the augmented Dickey–Fuller unit-root test of selected REE logarithmic returns including trend and intercept. The results indicate that variables are mostly stationary in the first difference at the 1% and 5% significance levels. The null hypothesis of a unit root is rejected for all REEs at the 1% significance level except for the Ce and Dy series. Only the Ce series result is stationary at a 5% level of significance. The Dy series is stationary in second differences at a 1% level of significance. The data are stationary and appropriate for further testing.

2. ARIMA Filter

In this study, each series was initially filtered by using an autoregressive moving average (ARMA) model to remove potential linear dependence. The time series usually exhibits strong periodical autocorrelation. Fitting linear models to the series is required. ARIMA models can be used when the time series is stationary. ARIMA models were selected in this study according to the Akaike information criterion (AIC) minimum value shown in Table 2. The empirical results demonstrated optimal ARIMA results after the AIC value was chosen. To examine whether residuals exhibit series correlation, this study conducted residual LM and Q tests. Majority of the series has no autocorrelation. The optimal ARMA model is shown in Table 3.

The results of the ARMA show that all the variables have no serial correlation. The p-values of the residual LM test are Ce (0.98), Eu (0.67), Nd (0.95), Pr (0.77), Sm (0.74), and Y (0.9). These p-values have levels of significance that are greater than 5% and 1%. The p-value of Dy is (0.33) at a 1% significance level. The p-value of the La variable displays a less than 1% significance level. This study also applied another autocorrelation test, the residual Q test. Findings show that the p-values of all variables pass at least a 5% significance level. Thus, ARIMA filtered residuals were free from linear dependence. In the next step, we examined whether the nonlinear dependence of the linearly filtered REE series could be attributed to an ARCH-type conditional heteroskedasticity.

3. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Filter

This paper employed a GARCH model to remove conditional heteroskedasticity. *Q2* test was used to detect whether serial correlation exists after GARCH testing. Jirasakuldech and Emekter

Table 1
Unit root test results

#	Variable names	Series before unit root testing			First difference			Second difference		
		ADF test statistics	lag	AIC	ADF test statistics	lag	AIC	ADF test statistics	lag	AIC
1	Ce	-2.7722	2	0.9902	-4.0761**	1	1.0437			
2	Dy	0.5246	5	7.1310	-1.1679	4	7.1147	-10.6448***	3	7.1094
3	Eu	-2.1018	1	8.1732	-6.9092***	0	8.1961			
4	La	-2.5024	1	0.9787	-5.5868***	0	1.0187			
5	Nd	-2.2554	1	4.4188	-6.2065***	0	4.4480			
6	Pr	-1.9901	1	4.5297	-6.9541***	0	4.5485			
7	Sm	-2.2722	2	2.2518	-5.0260***	1	2.2824			
8	Tr	-2.6198	1	10.0980	-6.4962***	0	10.1433			
9	Y	-2.9330	1	3.6718	-5.7596***	0	3.7327			

Note: ADF denotes the augmented Dickey–Fuller unit root test and AIC denotes the Akaike info criterion. *** Denotes a statistic is significant at the 1% level of significance; ** denotes 5%, * denotes 10% level of significance respectively. Source: Summarized by author.

Table 2
Result of ARIMA filtering

Variable names	ARIMA	AR(1)	p	AR(2)	p	AR(3)	p	MA(1)	p	MA(2)	p	AIC	Residual LM test	p	Residual Q test
Ce	(1,1,1)	0.77***	0.00					0.34**	0.02			1.02	0.77	0.67	No
Dy	(2,2,0)	-0.86***	0.00	-0.58***	0.00							7.31	23.71***	0.00	No
Eu	(3,1,2)	0.93***	0.00	1.04	0.00	0.39***	0.00	0.45***	0.00	0.99***	0.00	8.86	1.75	0.41	No
La	(1,1,0)	0.56***	0.00									1.00	1.61	0.44	No
Nd	(1,1,1)	0.06	0.67					0.65***	0.00			4.39	2.43	0.29	No
Pr	(1,1,1)	0.35**	0.01					0.82***	0.00			4.48	2.86	0.58	No
Sm	(2,1,1)	0.40*	0.07	0.21*	0.05			-0.29	0.21			2.25	1.24	0.87	No
Tb	(1,1,0)	0.43***	0.00									10.15	2.43	0.65	No
Y	(2,1,1)	0.18	0.34	0.33 **	0.02			0.83***	0.00			3.71	3.15	0.53	No

Note: 1. Q test to Lag (36), the significance level α = 1% as the criteria. 2. Residuals LM test: *** denotes rejection of null hypothesis at 1% significant level; ** denotes rejection of null hypothesis at 5% significant level; * denotes rejection of null hypothesis at 10% significant level. 3. Residuals LM test optimal lag number (4). 5. "No "denotes "no series correlation."

Source: Summarized by author

Table 3
ARMA model results for ARIMA residual

Variable names	ARIMA	AR(1)	p	AR(2)	p	MA(1)	p	MA(2)	p	AIC	Residual LM test	p	Residual Q test
Ce	(1,0,0)	0.02	0.78							1.01	0.03	0.98	No
Dy	(2,0,2)	0.78***	0.00	0.70***	0.00	-0.80***	0.00	0.40*	0.09	7.21	4.56	0.33	No
Eu	(2,0,2)	-0.09	0.18	-0.78***	0.00	0.08***	0.00	0.95	0.00	8.65	0.80	0.67	No
La	(1,0,2)	-0.96***	0.00			0.98***	0.00	-0.13**	0.22	0.89	26.21	0.00	No
Nd	(1,0,0)	0.001	0.99			0.76*	0.00			4.37	0.63	0.95	No
Pr	(1,0,1)	0.85***	0.00			-0.76**	0.00			4.46	1.80	0.77	No
Sm	(1,0,1)	-0.009	0.92							2.22	0.08	0.99	No
Tr	(1,0,0)	0.02	0.79							10.11	1.94	0.74	No
Y	(2,0,2)	0.06	0.42	0.73***		-0.06*	0.09	0.97***		3.62	1.00	0.90	No

Note: Lag of Q test (36) and the significance level α = 1% chosen as the criteria. *** Denotes a statistic is significant at the 1% level of significance; ** denotes 5%, * denotes 10% level of significance respectively. Optimal lag number of the residuals LM test is (4). "No" denotes "no series correlation".

Source: Summarized by author.

(2011) noted that nonlinear dependence is possibly present if the null hypothesis of independent and identically distributed (*iid*) variables is rejected for residuals from a linearly filtered series and a GARCH-filtered series. This study proceeded by testing whether deterministic chaos could possibly exist. The results indicate insignificant values in the ARCH-LM test. This finding indicates the absence of ARCH effects. Table 4 shows the empirical results of the ARCH- LM test for residuals from a linearly filtered series.

The Dy, La, Nd, Pr, and Y results are all significant, which indicates the rejection of the null hypothesis. Furthermore, this work tested an appropriate exponential GARCH (EGARCH) model based on the smallest AIC criterion to eliminate the ARCH effect. Table 5 indicates the autocorrelation of the EGARCH tests. All tests reveal insignificant values after fitting with an optimal EGARCH model, suggesting that the ARCH effect no longer exists and making the model effectively fits with the underlying series.

Table 4 Empirical result of ARCH effect test

#	Variable names	ARCH-LM test	p-value	Q^2 test
1	Ce	0.066687	0.796224	no series correlation
2	Dy	3657721***	0.000000	no series correlation
3	Eu	0.386152	0.983595	no series correlation
4	La	17.25774***	0.000033	no series correlation
5	Nd	15.58834**	0.003624	no series correlation
6	Pr	12.76597**	0.012478	no series correlation
7	Sm	0.441384	0.978951	no series correlation
8	Tr	4.256709	0.372377	no series correlation
9	Y	12.05198**	0.016969	no series correlation

Note: ARCH-LM test lag (4). *** denotes rejection of null hypothesis at 1% significant level; ** denotes rejection of null hypothesis at 5% significant level; * denotes rejection of null hypothesis at 10% significant level.

Table 5 EGARCH model result

#	Variable names	EGARCH	AIC	Autocorrelation test		
				ARCH-LM test	p-value	residual Q test
1	Dy	(2,4)	5.698144	3.318299	0.506038	no series correlation
2	La	(2,0)	(0.0030)	0.539189	0.462769	no series correlation
3	Nd	(2,2)	2.498588	1.634524	0.802574	no series correlation
4	Pr	(3,2)	3.054705	0.298949	0.989882	no series correlation
5	Y	(3,2)	2.141195	0.896312	0.925089	no series correlation

Note: ARCH-LM test lag (4) for the optimal lag number.

4. Empirical Results of the Chaos Effect

(1) BDS test

The BDS test is used to detect chaos behavior in residuals and to examine whether these data behave as *iid*. Brock et al. (1991) noted that the BDS test can be used to detect nonlinearity in econometric models. The original series of the observation is first examined by using the unit root test to remove nonstationarity. Linear dependence is eliminated through ARIMA model fitting. Conditional heteroskedasticity in the data is removed by using the ARCH test.

The GARCH test used in this paper eliminates the ARCH effect. BDS test statistics are then calculated for the residuals after filtering with the use of the GARCH model. The testing of the original series and the ARIMA-filtered residuals include nine variables. These variables are Ce, Dy, Eu, La, Nd, Pr, Tb, Sm, and Y. The residuals of GARCH filtering include five variables: Dy, La, Nd, Pr, and Y.

The results given in Table 6 reject the null hypothesis. Table 7 tabulates the empirical results of the ARIMA-filtered residuals. The BDS test calculated among m values 2 to 6 for the Ce and La series are significant at the 1% level. The BDS test for the Dy series passes at 0.5, 1.0, and 2.0 σ standard deviation at a 1% significant level. The p-values are significant at 1%, with m equal to 2 and 3, when the standard deviation is 1.5 σ. The p-values are significant at 5% and 10%, with m equal to 3 and 6, respectively. The Eu series is significant at the 10% level when $0.5 \leq \varepsilon/\sigma \leq 1.5$ and when m is from 3 to 6. These results differ from the BDS results of the original series. However, the null hypothesis is also rejected in ARIMA-filtered residuals. The following test is the empirical result of the BDS statistic test for GARCH-filtered residuals as summarized in Table 8.

The BDS results for Ce and Y GARCH-filtered residuals are significant. The p-values are mostly significant at the 1% level when m is 2 to 6. Y residual p-values are only significant at the 5% level when both m and standard deviation ε/σ are equal to 2. La p-values are significant at the 1% level when ε/σ is equal to 0.5. Dy p-values are at least significant at the 10% level when m is 2 to 5. Nonlinear dependence is possibly present if the series of GARCH-filtered residuals is proven to be non-*iid*. Deterministic chaos can possibly exist if the null hypothesis is rejected. However, Jirasakuldech and Emekter (2011) noted that BDS is possibly inefficient for the detection of weak nonlinearity.

This study also shows that the testing of the original series, the ARIMA-filtered residuals, and the GARCH-filtered residuals for Y and Ce rejected the null hypothesis. However, the remainder of the samples for GARCH-filtered residuals fails to reject the null hypothesis. The biased GARCH-filtered residuals indicate that the p-values of the data are smaller before the series standardization process is applied. The BDS test statistics of all the series are generally smaller than those of the series before standardization is applied. These results are consistent with the findings of Jirasakuldech and Emekter (2011).

According to Hsieh (1991), the BDS test can detect nonstationarity, linear dependence, nonlinear stochastic process, and chaos. However, the BDS test may not exactly determine the existence of chaotic phenomena. BDS rejections of *iid* do not provide any direct evidence of chaos (Jirasakuldech and Emekter, 2011). This paper conducted further testing through Hurst's (1951) R/S analysis to determine whether REE nonlinearity is consistent with a chaotic process.

Table 6
BDS test results before filtering

Series name	ε/σ	0,5		1		1,5		2	
	m	BDS	Prob.	BDS	Prob.	BDS	Prob.	BDS	Prob.
Ce	2	0.2230	0.0000***	0.2191	0.0000***	0.1767	0.0000***	0.1347	0.0000***
	3	0.3178	0.0000***	0.3404	0.0000***	0.2897	0.0000***	0.2298	0.0000***
	4	0.3564	0.0000***	0.4065	0.0000***	0.3608	0.0000***	0.2952	0.0000***
	5	0.3709	0.0000***	0.4428	0.0000***	0.4053	0.0000***	0.3460	0.0000***
	6	0.3743	0.0000***	0.4617	0.0000***	0.4327	0.0000***	0.3845	0.0000***
Dy	2	0.2052	0.0000***	0.2267	0.0000***	0.1735	0.0000***	0.0710	0.0000***
	3	0.2700	0.0000***	0.3429	0.0000***	0.2894	0.0000***	0.1196	0.0000***
	4	0.2862	0.0000***	0.4034	0.0000***	0.3655	0.0000***	0.1408	0.0000***
	5	0.2867	0.0000***	0.4347	0.0000***	0.4180	0.0000***	0.1429	0.0000***
	6	0.2811	0.0000***	0.4509	0.0000***	0.4591	0.0000***	0.1405	0.0000***
Eu	2	0.2052	0.0000***	0.2167	0.0000***	0.2059	0.0000***	0.1628	0.0000***
	3	0.2749	0.0000***	0.3293	0.0000***	0.3345	0.0000***	0.2783	0.0000***
	4	0.2907	0.0000***	0.3892	0.0000***	0.4139	0.0000***	0.3584	0.0000***
	5	0.2858	0.0000***	0.4200	0.0000***	0.4644	0.0000***	0.4137	0.0000***
	6	0.2725	0.0000***	0.4330	0.0000***	0.4971	0.0000***	0.4545	0.0000***
La	2	0.2255	0.0000***	0.2168	0.0000***	0.1797	0.0000***	0.1385	0.0000***
	3	0.3214	0.0000***	0.3356	0.0000***	0.2929	0.0000***	0.2355	0.0000***
	4	0.3616	0.0000***	0.4028	0.0000***	0.3632	0.0000***	0.3030	0.0000***
	5	0.3772	0.0000***	0.4398	0.0000***	0.4061	0.0000***	0.3502	0.0000***
	6	0.3822	0.0000***	0.4594	0.0000***	0.4325	0.0000***	0.3897	0.0000***
Nd	2	0.2020	0.0000***	0.2119	0.0000***	0.1886	0.0000***	0.1309	0.0000***
	3	0.2640	0.0000***	0.3206	0.0000***	0.3044	0.0000***	0.2280	0.0000***
	4	0.2789	0.0000***	0.3716	0.0000***	0.3731	0.0000***	0.2963	0.0000***
	5	0.2774	0.0000***	0.3916	0.0000***	0.4120	0.0000***	0.3441	0.0000***
	6	0.2706	0.0000***	0.3949	0.0000***	0.4334	0.0000***	0.3800	0.0000***
Pr	2	0.1987	0.0000***	0.2126	0.0000***	0.1843	0.0000***	0.1287	0.0000***
	3	0.2588	0.0000***	0.3201	0.0000***	0.2994	0.0000***	0.2203	0.0000***
	4	0.2703	0.0000***	0.3708	0.0000***	0.3692	0.0000***	0.2842	0.0000***
	5	0.2664	0.0000***	0.3908	0.0000***	0.4087	0.0000***	0.3303	0.0000***
	6	0.2567	0.0000***	0.3943	0.0000***	0.4293	0.0000***	0.3649	0.0000***
Sm	2	0.2097	0.0000***	0.2224	0.0000***	0.2018	0.0000***	0.1143	0.0000***
	3	0.2612	0.0000***	0.3347	0.0000***	0.3284	0.0000***	0.2186	0.0000***
	4	0.3003	0.0000***	0.3882	0.0000***	0.4058	0.0000***	0.3045	0.0000***
	5	0.2996	0.0000***	0.4116	0.0000***	0.4516	0.0000***	0.3749	0.0000***
	6	0.2932	0.0000***	0.4197	0.0000***	0.4774	0.0000***	0.4304	0.0000***
Tb	2	0.1606	0.0000***	0.2019	0.0000***	0.1784	0.0000***	0.1317	0.0000***
	3	0.1554	0.0000***	0.2690	0.0000***	0.2967	0.0000***	0.2322	0.0000***
	4	0.1763	0.0000***	0.2788	0.0000***	0.3713	0.0000***	0.3075	0.0000***
	5	0.1596	0.0000***	0.2698	0.0000***	0.4171	0.0000***	0.3643	0.0000***
	6	0.1423	0.0000***	0.2526	0.0000***	0.4475	0.0000***	0.4086	0.0000***
Y	2	0.2179	0.0000***	0.2224	0.0000***	0.1609	0.0000***	0.1282	0.0000***
	3	0.3033	0.0000***	0.3435	0.0000***	0.3131	0.0000***	0.2376	0.0000***
	4	0.3319	0.0000***	0.4100	0.0000***	0.4081	0.0000***	0.3307	0.0000***
	5	0.3386	0.0000***	0.4422	0.0000***	0.4762	0.0000***	0.4096	0.0000***
	6	0.3346	0.0000***	0.4550	0.0000***	0.5223	0.0000***	0.4763	0.0000***

Note: The embedding dimensions (m) are from 2 to 6. The distance measure approximately
Source: Summarized by author.

Table 7
Empirical result of BDS statistic test of ARIMA filtered residuals

Series name	ε/σ	0,5		1		1,5		2	
	m	BDS	Prob.	BDS	Prob.	BDS	Prob.	BDS	Prob.
Ce	2	0.0945	0.0000***	0.0850	0.0000***	0.0418	0.0000***	0.0375	0.0000***
	3	0.1228	0.0000***	0.1359	0.0000***	0.0765	0.0000***	0.0667	0.0000***
	4	0.1272	0.0000***	0.1745	0.0000***	0.0974	0.0001***	0.0675	0.0037***
	5	0.1319	0.0000***	0.2101	0.0000***	0.1395	0.0000***	0.0948	0.0015***
	6	0.1294	0.0000***	0.2446	0.0000***	0.1716	0.0000***	0.1163	0.0011***
Dy	2	0.0458	0.0000***	0.0322	0.0086***	0.0305	0.0019***	0.0275	0.0005***
	3	0.0763	0.0000***	0.0625	0.0018***	0.0536	0.0034***	0.0417	0.0071***
	4	0.0795	0.0000***	0.0707	0.0038***	0.0534	0.0363**	0.0343	0.1339***
	5	0.0715	0.0000***	0.0697	0.0078***	0.0388	0.2116	0.0152	0.6082***
	6	0.0576	0.0000***	0.0868	0.0008***	0.0649	0.0643*	0.0405	0.2528***
Eu	2	0.0302	0.0003***	0.0173	0.1239	0.0109	0.2829	(0.0010	0.8878
	3	0.0326	0.0000***	0.0361	0.0258**	0.0360	0.0415**	0.0140	0.3305
	4	0.0281	0.0000***	0.0477	0.0063***	0.0524	0.0232**	0.0286	0.1676
	5	0.0171	0.0000***	0.0377	0.0221**	0.0535	0.0421**	0.0329	0.2050
	6	0.0093	0.0000***	0.0332	0.0208**	0.0529	0.0574*	0.0352	0.2424
La	2	0.0403	0.0013***	0.0559	0.0000***	0.0663	0.0000***	0.0396	0.0000***
	3	0.0741	0.0000***	0.0894	0.0000***	0.1164	0.0000***	0.0777	0.0000***
	4	0.0886	0.0000***	0.1309	0.0000***	0.1555	0.0000***	0.1069	0.0000***
	5	0.0871	0.0000***	0.1662	0.0000***	0.1824	0.0000***	0.1262	0.0001***
	6	0.0771	0.0000***	0.1908	0.0000***	0.1970	0.0000***	0.1372	0.0002***
Nd	2	0.0832	0.0000***	0.0477	0.0004***	0.0261	0.0209**	0.0069	0.4172***
	3	0.1434	0.0000***	0.1160	0.0000***	0.0784	0.0001***	0.0345	0.0323***
	4	0.1559	0.0000***	0.1739	0.0000***	0.1337	0.0000***	0.0851	0.0002***
	5	0.1495	0.0000***	0.1966	0.0000***	0.1472	0.0000***	0.0954	0.0009***
	6	0.1347	0.0000***	0.2174	0.0000***	0.1731	0.0000***	0.1286	0.0001***
Pr	2	0.0756	0.0000***	0.0585	0.0000***	0.0333	0.0039**	0.0361	0.0001***
	3	0.1203	0.0000***	0.1139	0.0000***	0.0712	0.0007***	0.0641	0.0004***
	4	0.1440	0.0000***	0.1734	0.0000***	0.1222	0.0000***	0.1067	0.0000***
	5	0.1398	0.0000***	0.1898	0.0000***	0.1350	0.0001***	0.1366	0.0000***
	6	0.1292	0.0000***	0.2100	0.0000***	0.1603	0.0000***	0.1597	0.0000***
Sm	2	0.0352	0.0078***	0.0039	0.7166	(0.0142	0.1219	(0.0171	0.0349**
	3	0.0689	0.0000***	0.0281	0.1403	(0.0141	0.4295	(0.0266	0.1016
	4	0.0720	0.0000***	0.0394	0.1196	(0.0176	0.4961	(0.0400	0.0999*
	5	0.0635	0.0000***	0.0480	0.1025	(0.0246	0.4563	(0.0557	0.0810*
	6	0.0584	0.0000***	0.0592	0.0611*	(0.0213	0.5844	(0.0605	0.1180
Tb	2	0.0705	0.0000***	0.0356	0.0121**	0.0398	0.0006***	0.0222	0.0073**
	3	0.1001	0.0000***	0.0455	0.0382**	0.0514	0.0121**	0.0339	0.0341**
	4	0.1129	0.0000***	0.0822	0.0013**	0.0881	0.0028**	0.0396	0.087*
	5	0.1045	0.0000***	0.0975	0.0002***	0.0981	0.0018**	0.0390	0.1828
	6	0.0889	0.0000***	0.0842	0.0006***	0.0793	0.019**	0.0234	0.4944
Y	2	0.1030	0.0000***	0.0914	0.0000***	0.0716	0.0000***	0.0303	0.0002***
	3	0.1480	0.0000***	0.1479	0.0000***	0.1255	0.0000***	0.0602	0.0002***
	4	0.1586	0.0000***	0.1866	0.0000***	0.1675	0.0000***	0.0845	0.0004***
	5	0.1519	0.0000***	0.2079	0.0000***	0.2020	0.0000***	0.1119	0.0003***
	6	0.1410	0.0000***	0.2112	0.0000***	0.2228	0.0000***	0.1318	0.0004***

Note: The embedding dimensions (m) are from 2 to 6. The distance measure approximately equals to 0.5σ, 1.0σ, 1.5σ and 2.0σ, where σ is the standard deviation of the series. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Source: Summarized by author.

Table 8

Empirical result of BDS statistic test of GARCH filtered residuals

Series name	ε/σ	0,5		1		1,5		2	
	m	BDS statistics	Prob.	BDS statistics	Prob.	BDS statistics	Prob.	BDS statistics	Prob.
Ce	2	0.1029	0.0000***	0.0776	0.0000***	0.0584	0.0000***	0.0419	0.0000***
	3	0.1347	0.0000***	0.1272	0.0000***	0.1069	0.0000***	0.0761	0.0000***
	4	0.1442	0.0000***	0.1703	0.0000***	0.1347	0.0000***	0.0803	0.0004***
	5	0.1487	0.0000***	0.2172	0.0000***	0.1786	0.0000***	0.1092	0.0002***
	6	0.1458	0.0000***	0.2531	0.0000***	0.2175	0.0000***	0.1309	0.0001***
Dy	2	0.0000	0.9988	(0.0139)	0.2128	(0.0144)	0.1391	(0.0187)	0.0126**
	3	0.0053	0.4496	(0.0133)	0.4055	(0.0175)	0.2962	(0.0272)	0.0598*
	4	0.0050	0.2902	(0.0115)	0.5020	(0.0185)	0.3957	(0.0349)	0.0926*
	5	0.0010	0.7322	(0.0210)	0.1905	(0.0326)	0.1857	(0.0510)	0.0511*
	6	(0.0002)	0.8860	(0.0161)	0.2489	(0.0240)	0.3539	(0.0406)	0.1823
Y	2	0.0688	0.0000***	0.0328	0.0083***	0.0199	0.0347**	0.0131	0.0460**
	3	0.0887	0.0000***	0.0841	0.0000***	0.0560	0.0015***	0.0373	0.0050***
	4	0.0932	0.0000***	0.1175	0.0000***	0.0807	0.0011***	0.0592	0.0033***
	5	0.0830	0.0000***	0.1290	0.0000***	0.1031	0.0007***	0.0764	0.0041***
	6	0.0713	0.0000***	0.1277	0.0000***	0.1238	0.0003***	0.0917	0.0048***
La	2	0.0247	0.0002***	0.0065	0.5217	0.0010	0.9086	0.0024	0.6757
	3	0.0300	0.0000***	0.0162	0.2338	(0.0029)	0.8363	0.0022	0.8398
	4	0.0200	0.0000***	0.0149	0.2783	(0.0078)	0.6676	0.0001	0.9950
	5	0.0109	0.0000***	0.0125	0.3057	(0.0172)	0.3983	(0.0083)	0.6897
	6	0.0042	0.0000***	0.0074	0.4580	(0.0201)	0.3432	(0.0066)	0.7868
Nd	2	(0.0105)	0.3275	(0.0086)	0.5038	(0.0066)	0.5363	0.0023	0.7660
	3	(0.0079)	0.4646	(0.0043)	0.8219	(0.0029)	0.8363	0.0022	0.4188
	4	(0.0031)	0.7043	0.0038	0.8595	(0.0078)	0.6676	0.0001	0.3965
	5	(0.0027)	0.6251	0.0019	0.9265	(0.0172)	0.3983	(0.0083)	0.4862
	6	(0.0014)	0.6738	0.0076	0.6927	(0.0201)	0.3432	(0.0066)	0.6072

Note: The embedding dimensions (m) are from 2 to 6. The distance measure approximately equals to 0.5σ, 1.0σ, 1.5σ and 2.0σ, where σ is the standard deviation of the series. ***, **, and * indicate significance at the 1%, 5%, and 10%.

Source: Summarized by author.

(2) R/S analysis

R/S analysis can distinguish a random series from a fractal series irrespective of the distribution of the underlying series. The Hurst (*H*) exponent, which is calculated by using R/S analysis, can be a useful factor in determining the characteristic of a time series. An estimation of a valid *H* exponent is that the simulated *H* exponent after scrambling the data would be significantly closer to 0.5 than that before the scrambling process. The values of the *H* exponent for the time series involved in the experiment are listed in Table 9.

Table 9 Empirical result of the R / S analysis

Series type	Variable names	Theoretical Hurst exponent	Simulated Hurst Exponent	Result
Before filtering	Ce	0.750347	0.981194	$0.5 \le H \le 1$
	Dy	0.537482	0.959007	$0.5 \le H \le 1$
	Eu	0.745735	0.984522	$0.5 \le H \le 1$
	La	0.761459	0.981656	$0.5 \le H \le 1$
	Nd	0.678557	0.980515	$0.5 \le H \le 1$
	Pr	0.661270	0.977045	$0.5 \le H \le 1$
	Sm	0.685154	0.990104	$0.5 \le H \le 1$
	Tb	0.650864	0.995779	$0.5 \le H \le 1$
	Y	0.706579	0.978878	$0.5 \le H \le 1$
ARIMA filtered	Ce	0.004046	**0.506908	$0.5 \le H$
	Dy	(0.053241)	0.247232	$0 \le H \le 0.5$
	Eu	(0.037003)	**0.530266	$0.5 \le H$
	La	0.019411	**0.530644	$0.5 \le H$
	Nd	(0.021435)	**0.561324	$0.5 \le H$
	Pr	0.026215	**0.585019	$0.5 \le H$
	Sm	0.020272	**0.520733	$0.5 \le H$
	Tb	0.035146	**0.483840	$0 \le H$
	Y	0.021288	**0.493007	$0 \le H$
GARCH filtered	Ce	0.004987	**0.454562	$0 \le H$
	Dy	0.016901	**0.435900	$0 \le H \le 0.5$
	Eu	(0.009155)	**0.534762	$0.5 \le H$
	La	(0.008717)	**0.569438	$0.5 \le H$
	Nd	0.015798	**0.631714	$0.5 \le H \le 1$

Note: * denotes closer H with 0.5. Source: Summarized by author.

The result shows that Dy has the lowest value for the ARIMA-filtered residuals, while Ce and Dy have the lowest values for the GARCH-filtered residuals. This result indicates that these time series represent antipersistent processes dominated by high volatility. The GARCH-filtered residual of Nd has the highest H exponent. The scrambled H exponent of the ARIMA-filtered series and the GARCH-filtered residuals are all close to 0.5. The valid H exponent should be close to 0.5 based on the R/S test. According to Jirasakuldech and Emekter (2011), the best prediction result is the value with the highest H exponent. The best prediction of Nd has the highest H exponent.

All the H exponents are greater than 0.5 before and after the scrambling of the original series of data. This result can be explained by the possibility that R/S analysis can be biased under two major departures: nonstationarity and short-memory process. The original series is nonstationary. This fact might explain why the H exponent has values greater than 0.5. According to Peters (1996), the values of the original series represent persistent and trend-reinforcing processes.

(3) Correlation dimension analysis

Correlation exponent values are calculated against corresponding m values to examine whether chaos exists. The process under investigation is deterministic if the correlation exponent yields a finite value as m increases. The values of the correlation dimension for the original time series involved in the experiment are listed in Table 10. These phenomena converge if dimension (D) increases or if D is lower than *m*. According to Moshiri and Foroutan (2006), the fractal dimension should eventually converge in its value as *m* increases. For example, the correlation dimension of Ce to Eu increased with the rise in *m*. The underlying data are consistent with chaos if the correlation dimensions converge as *m* gradually increases. The result from the ARIMA-filtered series was also analyzed. Table 11 shows the correlation dimension results of this series. For example, the correlation exponent of La to Sm yields a finite value as *m* increases. The results for Ce, Pr, Sm, and Y are converging from the beginning of *m*, which suggests that the underlying data of the original series are consistent with chaos. Table 12 shows the GARCH-filtered series results for the correlation dimension of this series.

5. Empirical results of ANNs

This section presents the neural network structure of the data with the minimum value of MSE. The results of the ANN models are also compared. Table 13 shows the best neural network structure performance for each index. The results indicate that most of the variables have two hidden layers. Chester (1990) and Zhang (1994) noted that networks with two hidden layers can model data structure more accurately than networks with one hidden layer. Zhang et al. (1998) stated that experiments or trial-and-error methods are suitable for the determination of the number of hidden neurons. According to the minimum value of MSE, networks with four hidden neurons are suitable for this study. This study tested the values from 0.1 to 0.7 to determine the appropriate learning rate. The findings differ for each variable. The result for Ce, Nd, Pr, and Tr is 0.1. The result for Dy, La, and Y is 0.3. The result for Sm is 0.5, whereas that for Eu is 0.7. To finalize the establishment of suitable networks, this study tested different estimation numbers such as 1000, 3000, and 10000. The estimated iteration numbers are mostly 1000. Only the Sm series result is 3000.

Table 10

Empirical results of the correlation dimension for series after unit root test

Series name	m						
	4	5	6	7	8	9	10
Ce	3.488	4.560	3.928	4.962	4.410	5.181	4.748
Dy	2.368	2.254	2.314	3.122	2.948	3.507	5.684
Eu	1.893	2.674	2.600	4.152	5.415	6.065	5.603
La	5.068	5.183	6.610	5.749	6.465	6.139	4.732
Nd	2.743	2.910	2.817	4.602	6.032	4.393	4.737
Pr	1.147	1.520	1.832	2.542	2.983	3.634	2.777
Sm	0.848	2.111	2.211	2.343	2.739	2.960	3.519
Tb	3.106	3.003	3.230	3.227	3.863	4.179	5.200

Note: "m" denotes the embedding dimensions.

Source: Summarized by author.

Table 11

Correlation dimension empirical results of the ARIMA filtered series

Series names	4	5	6	7	8	9	10
Ce	1.669	2.024	3.764	4.252	4.271	5.435	6.403
Dy	3.030	5.046	4.038	5.483	6.447	4.121	5.614
Eu	4.456	4.267	6.000	5.908	5.241	3.561	5.306
La	0.203	0.907	1.792	3.242	4.699	5.758	6.332
Nd	3.374	4.606	4.440	4.871	4.890	5.460	6.610
Pr	2.095	2.150	2.239	2.224	2.717	3.214	3.353
Sm	1.240	2.103	2.315	3.626	3.056	4.391	4.195
Tb	0.932	1.590	4.706	6.710	7.398	6.065	6.407

Note: "m" denotes the embedding dimensions.

Source: Summarized by author.

Table 12

Correlation dimension empirical results of the GARCH filtered series

Series names	m						
	4	5	6	7	8	9	10
Ce	1.568	2.610	4.971	5.834	4.530	5.808	5.603
Dy	4.414	3.635	6.419	5.758	7.398	5.644	6.377
Eu	3.920	4.119	5.714	5.443	3.001	5.826	6.318
La	2.582	2.355	2.505	3.162	4.705	3.989	4.404
Nd	3.347	4.374	5.482	6.000	7.398	6.307	6.000

Note: "m" denotes the embedding dimensions.

Source: Summarized by author.

Table 13 Neural network architecture

#	Variable names	Proportion of training sample	Hidden layer(s)	Hidden neurons	Learning rate	Iterations
1	Ce	90%	2	4	0.1	1000
2	Dy	90%	2	4	0.3	1000
3	Eu	90%	1	4	0.7	1000
4	La	90%	2	4	0.3	1000
5	Nd	90%	2	4	0.1	1000
6	Pr	90%	2	4	0.1	1000
7	Sm	90%	2	4	0.5	3000
8	Tb	90%	2	4	0.1	1000
9	Y	90%	2	4	0.3	1000

Table 14 compares the estimated outcomes of BPN and TDRNN. The analysis of each forecasting performance is based on data errors between a desired and a neural network output value. The TDRNN model performed better in testing the REEs according to the empirical results that used two kinds of ANN models. The values of the TDRNN's MSE are mostly lower than those of the BPN models. The lowest values of TDRNN are Tr (0.0653), Y (0.0895), and

Nd (0.0972). However, the BPN model outperformed the TDRNN model in the case of Eu. This finding indicates that the TDRNN model outperformed the BPN model in REE data testing. This result is consistent with the findings of Kim (1998), which show that TDRNN is more capable of forecasting than other neural network models.

The data in Table 15 validate the initial findings that the TDRNN model consistently outperforms the BPN model and that the REE price value could be predicted more accurately according to the lowest RMSE values. This study also found that TDRNN improves the generalization of the error metric. This finding is consistent with the conclusion of Cohen et al. (1995) that TDRNN has potential for improving generalization capabilities. MAE results mostly pointed to the BPN model. We acknowledge the fact that BPN can also have a better learning rate. Thus, the researchers realized that the selection of the error metric is very important in making accurate predictions. Therefore, having as many metric and model comparisons as possible in forecasting analysis is beneficial for making the best decision.

This paper also ranked the results of error metrics to determine which variable was estimated the best among the BPN and TDRNN simulations. The results are detailed in Table 16. The findings reveal that the BPN model of Nd, Tb, and Y performed better based on the RMSE metric. Meanwhile, Pr, La, and Dy produced better results in measuring MAE. Pr, Nd, and Dy exhibited better performance for RMSE based on the TDRNN performance. Meanwhile, Nd, La, and Dy exhibited better performance in the MSE metric. The lowest ranking frequency in the results showed that Nd, Pr, La, and Dy performed better than the others in the time series. Thus, the proposed model is more suitable for Dy, Pr, La, and Nd.

Table 14 ANN's testing results

Types	Parameters Setting	BPN	TDRNN
	Hidden Nodes	10	10
	Transfer Function	Sigmoid	Sigmoid
	Learning Rate	0.7	0.7
	Maximum Epochs	1,000	1,000
	Testing Data	10%	10%
Ce	MSE	2.3749	**2.0451
Dy	MSE	1.5608	**1.1085
Eu	MSE	**0.0487	1.1918
La	MSE	1.5998	**1.1039
Nd	MSE	0.1244	**0.0972
Pr	MSE	0.5049	**0.1146
Sm	MSE	0.5725	**0.5128
Tr	MSE	0.1048	**0.0653
Y	MSE	0.1007	**0.0895

Note: ** denotes better performance consequence based on the testing criteria, "BPN" denotes Back-Propagation Neural Network, and "TDRNN" denotes Time-Lag Recurrent Neural Network.

Table 15 Comparison of forecasting indices

	RMSE		MAE	
	BPN	TDRNN	BPN	TDRNN
Ce	0.6390	**0.2763	0.6264	**0.5688
Dy	0.4718	**0.1915	**0.0203	0.0373
Eu	0.6762	**0.3073	**0.0501	0.0553
La	0.4708	**0.2086	**0.0189	0.0352
Nd	0.3487	**0.1905	0.0462	**0.0143
Pr	0.4185	**0.2070	**0.0151	0.0590
Sm	0.5941	**0.2889	**0.0541	0.0579
Tb	0.2921	**0.2916	0.0942	**0.0863
Y	0.3447	**0.2934	**0.1033	0.1512

Note: RMSE stands for root mean square error and MAE stands for mean absolute error.
** denotes better performance consequence based on comparison of BPN and TDRNN.

Table 16 Forecasting performance ranking of REEs

	BPN		BPN		TDRNN		TDRNN	
	RMSE	Ranking	MAE	Ranking	RMSE	Ranking	MAE	Ranking
Ce	0.6390	8	0.6264	9	0.2764	5	0.5688	9
Dy	0.4718	6	0.0204	3	0.1916	2	0.0373	3
Eu	0.6762	9	0.0501	5	0.3074	9	0.0553	4
La	0.4708	5	0.0190	2	0.2086	4	0.0352	2
Nd	0.3487	3	0.0462	4	0.1906	1	0.0143	1
Pr	0.4185	4	0.0152	1	0.207	3	0.0590	6
Sm	0.5941	7	0.0542	6	0.289	6	0.0579	5
Tb	0.2921	1	0.0942	7	0.2917	7	0.0863	7
Y	0.3447	2	0.1034	8	0.2935	8	0.1512	8

Note: RMSE stands for root mean square error and MAE stands for mean absolute error.

V. Conclusion

This study primarily aims to determine chaotic tendencies and to predict REE returns. These elements have recently received considerable attention because of the increasing returns that they yield. These elements are key components in green energy technologies and in other high-technology applications, which makes them crucial resources. This study also aims to test whether the REE time series prices behave in chaos. Three different approaches were employed. The BDS test was used to determine whether the data is nonlinear. R/S analysis was employed to confirm chaotic phenomenon. Correlation dimension was utilized to determine the degree of complexity of a time series. Another objective of this study is to utilize two ANN models, namely, BPN and TDRNN, to determine REE price behavior and to provide investors with valuable information through the accurate prediction of their returns according to related factors.

To employ BDS, R/S and correlation dimension tests, this study followed some steps based on previous literature. Initial filtering was executed to remove nonstationarity through the unit root test. Linear dependence was eliminated through the ARMA model. Conditional heteroskedasticity was removed through the ARCH and GARCH models.

The BDS test shows significant findings for the original time series. ARIMA-filtered residuals also reveal significant results. The final step for the BDS test was for the GARCH-filtered residuals. The result indicates a more significant value for the Ce and Y series in each *m*. This study also utilized R/S analysis to determine whether REE nonlinearity is consistent with a chaotic process.

All the *H* exponents for the original series of data were greater than 0.5 before and after data scrambling. This result can be interpreted under two major departures: nonstationarity and short-memory process. The original series is nonstationary. This fact might be the reason why the *H* exponent is greater than 0.5. All the 14 scrambled *H* exponents of the ARIMA- and GARCH-filtered residuals are significantly asymptotic to 0.5 except for the ARIMA-filtered series of Dy. This result highlights that REE prices are fractal and chaotic. Based on the correlation dimension test, this research concludes that the underlying REE data are consistent with chaos, which suggests that conventional linear models are inappropriate for their analysis.

The TDRNN model consistently outperformed the BPN model in terms of REE price prediction accuracy. This study proved that an ANN has powerful prediction capacity. Therefore, the use of an ANN as a forecasting tool for individual investors and fund managers is a practical measure that has significant advantages over the use of other prediction techniques.

Numerous individuals including researchers, investment professionals, and average investors are continually seeking a market that will yield them high returns. This paper aims to inspire investors to invest in the REE market and to help manufacturers in making plans and strategic decisions related to the current high technology.

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Appendix

Rare earth metals' application

REE	Symbol	Application
Scandium	Sc	High-strength Al–Sc alloys, electron beam tubes.
Yttrium	Y	Capacitors, phosphors, microwave filters, glasses, oxygen sensors, radars, lasers, superconductors, fiber optics, ceramics, magnets.
Lanthanum	La	Batteries, glasses, ceramics; car catalysts, phosphors, pigments, accumulators, catalysts hydrocarbon cracking, galvanizing, polishing powders.
Cerium	Ce	Polishing powders, ceramics, phosphors, glasses, catalysts, pigments, misch metal, UV filters, batteries, catalysts hydrocarbon cracking, catalysts automotive, metal alloy modifiers, plating.
Praseodymium	Pr	Ceramics, glasses, pigments, batteries, catalysts hydrocarbon cracking, magnets.
Neodymium	Nd	Constant magnets, catalysts, IR filters, pigments for glass, lasers, batteries.
Promethium	Pm	Sources for measuring devices, miniature nuclear batteries, phosphors.
Samarium	Sm	Constant magnets, microwave filters, nuclear industry.
Europium	Eu	Phosphors, fiber optics.
Terbium	Tb	Phosphors, fiber optics, magnetic disk data storage, magneto- strictive alloys.
Dysprosium	Dy	Phosphors, ceramics, nuclear industry, magnets, magneto- strictive alloys.
Holmium	Ho	Ceramics, lasers, nuclear industry.
Erbium	Er	Ceramics, dyes for glass, optical fibers, lasers, nuclear industry, metal alloy modifiers.
Ytterbium	Yb	Metallurgy, chemical industry.
Lutecium	Lu	Single-crystal scintillators.
Thulium	Tm	Electron beam tubes, visualization of images in medicine.
Gadolinium	Gd	Visualization of images in medicine.

Source: Organized by the author.[15]

[15] Naumov, 2008. "Review of the World Market of Rare Earth Metals" Russian Journal of Non-Ferrous Metals 49; Steve, 2010. "Rare Earth Materials: How scarce they are?" Spring 2010 Management Conference.

On the Intricacies of Cash Flow based Corporate Valuation

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Abstract

The current era of "convergence through connectivity" is slowly but certainly acknowledging the contribution of the so-called "intangibles" like brands, copyrights & patents, human & intellectual capital etc. to the bottomlines of companies. As an obvious corollary, issues relating to the valuation of such assets are surfacing with unprecedented regularity. Valuation of such assets posits an intriguing challenge for the accounting fraternity that is entrenched in the traditional ascendancy of "reliability" over "relevance".

"Discounted Cash Flow" is ubiquitous in financial valuation. In fact, this technique constitutes the cornerstone of contemporary valuation theory. The robustness of the model as well as its compatibility with the conventional two dimensional risk-return framework of investment appraisal make it immensely suited to a multitude of asset/liability valuations. Accounting standards across the globe recognize the efficacy of this model and advocate its use, wherever practicable. FAS 141 & 142 of the United States & IAS 39 that relate to the accounting of intangible assets also recommend use of DCF methodology for imputing a value to such assets. FAS 157 read with Concept Paper 7 mandate its use for ascertaining "fair value" of assets in certain cases. It is pertinent to note that the usual option pricing methods (including Black Scholes) also make use of discounted cash flows for calculating instantaneous option premia. However, like all models, DCF is not without its flaws. The model presupposes the existence of several unrealistic and rigid assumptions including, in particular, the existence of an acceptable "measure of risk" which is such that it can be integrated with the "discount" rate.

In this article, we attempt to address all these issues. We start by highlighting the variants of the DCF technique and the consequential versatility. This enables us to perform a dissection of this model and adduce its anatomy. While on this, we also explore interrelationships of DCF with other extant methods of valuations that include economic profit, residual income and income multipliers. As is inevitable, the DCF methodology has its own spectrum of limitations. While concluding this article, we present some of the important shortcomings of this model.

I. Introduction

"Discounted Cash Flow" is ubiquitous insofar as asset valuation goes with the method possessing the flexibility, adaptability and robustness to value literally, at least in theory, any asset under the sun, be it a security, project, corporate or an intangible or any combination thereof. In fact, the nexus between "Discounted Cash Flow" and valuation is so proximate that practitioners have ascribed a distinct identity to the valuation so obtained as "intrinsic" value. Its compatibility with the conventional two dimensional risk-return framework of investment appraisal makes it immensely suited to a multitude of valuation exercises. Accounting standards across the globe recognize the efficacy of this model and advocate its use, wherever practicable. FAS 141 & 142 of the United States & IAS 39 that relate to the accounting of intangible assets also recommend use of DCF methodology for imputing a value to such assets. FAS 157 read with Concept Paper 7 of the United States mandate its use for ascertaining "fair value" of assets in certain cases. It is pertinent to note that the usual option pricing methods (including Black Scholes) also make use of discounted cash flows for calculating instantaneous option premia.

The elegance of the method lies in its perceived simplicity – one merely projects the anticipated cash flows from the asset and estimates the return that may be desired commensurate with the risk profile of the projected cash flows and the asset value is spontaneous. Stated symbolically,

$$\text{Intrinsic Value} = \sum_{i=0}^{n} C_i e^{-r_i t_i} \qquad (1)$$

where C_i is the i^{th} cash flow occurring at time instant t_i of a series of n cash flows from the asset and r_i is the annualized interest rate (with continuous compounding) corresponding to a maturity of t_i (which is measured in years).

However, God could surely not have made "money matters" so uncomplicated and undemanding and, indeed, it is not so – while the computation of intrinsic value is the conventional "child's play", the estimation of inputs to the model is beset with numerous complexities and nuances and it is at this point that the professional's wisdom is truly tested. Not only does one face the intrinsic vagaries of "future" in making projections of inputs but one needs also to address the equally vital issue of identifying the appropriate inputs compatible with the "valuation" exercise envisaged. Needless to say, the nature of the inputs would vary with the type of asset to be valued.

The bottomline is that DCF is also a model and like all models it cannot simulate "reality" to exactness. Were it to be otherwise, then the model would also encompass the evolution equations of "reality" enabling it to project reality, which is surely not the case.

DCF is not without its flaws. The model presupposes the existence of several unrealistic and rigid assumptions including, in particular, the existence of an acceptable "measure of risk" which is such that it can be integrated with the "discount" rate. In this article, we attempt to address all these issues. In Section 2, we highlight the versatility of the DCF technique by elucidating its adaptability to value securities, projects, corporates and intangibles as well. This enables us to perform a dissection of this model and adduce its anatomy. While on this, we explore interrelationships of DCF with other extant methods of valuations that include income multipliers, residual income, accrual accounting based methods etc. In today's world of "fly by night" corporate operators, it is paramount to examine the susceptibility of a model to manipulations. We also examine this facet of the DCF model by conducting a comprehensive sensitivity analysis with respect to the input variables that include estimated/projected cash flows, discount rates, horizon values, the existence of abandonment options etc. As is inevitable, the DCF methodology has its own spectrum of limitations. While concluding this article in Section 3, we present some of the important shortcomings of this model and make recommendations on its possible upgradations to enhance its efficacy and reliability.

II. Value, Corporate Valuation & Drivers of Value

"Value" in commercial parlance connotes the "worth" of an asset or liability or a business enterprise. "Corporate Valuation" is, therefore, the process of ascertaining the worth of a corporate (company). Several approaches to corporate valuation have been advocated in the literature e.g.

(i) cash flow based methods;
(ii) income based methods;
(iii) asset based methods;
(iv) using comparables;
(v) option based valuations.

However, as has been elucidated in the preceding section, cash flow based methods predominantly find favour with academicians, professionals as well as practitioners because of their sound rationale, perceived simplicity and versatility. These methods essentially value the company simply by discounting an appropriate stream of future cash flows at a discount rate that is reflective of the risk profile of the stream of cash flows being discounted. The cash flow based methods manifest themselves in various formats that are tabulated below for easy reference:

S No	Model	Measure	Discount Factor
1	Enterprise DCF (FCF)	Free Cash Flow (FCF)	Weighted Av CoC (WACC)
2	Adjusted Present Value (APV)	Free Cash Flow (FCF)	Unlevered CoE (k_u)
3	Capital Cash Flow (CCF)	Capital Cash Flow (CCF)	Unlevered CoE (k_u)
4	Equity Cash Flow (ECF)	Equity Cash Flow (ECF)	Levered CoE (k_e)

In addition to the above cash flow based methods, a related method envisages the discounting of "economic profit (EP)" at the WACC.

Each of these methods has its set of merits and demerits. The FCF Model has the advantage of being versatile enough to value the company on a consistent basis either through the overall company cash flows or by aggregating the values of the constituent projects/units/segments of the company by discounting their respective cash flows at the WACC. Being cash flow based, FCF is also less amenable to manipulations through accounting policy changes etc. However, the "consistency" of the FCF Model can sustain only if the company pursues the financial policy of a stable capital structure. In the event that significant changes in the company's capital structure have been effectuated e.g. through mergers/acquisitions, the APV Model yields better results since the method involves the segregating of the company's cash flows into various components on the basis of their respective risk profiles and thereafter discounting each of them separately at the discount rate that is commensurate with the risk of the respective corresponding cash flow stream. Thus, APV does not embed the risk of capital structure related cash flows in the cost of capital, as is usually the case. It specifically forecasts each such cash flow and works out the present value thereof by discounting at the corresponding risk adjusted rate. The CCF Model has the limitation of combining the FCF and the Interest Tax Shields (ITS) into one number making it difficult to make horizontal and vertical comparisons. The ECF Model has a similar shortcoming in the sense that it also mixes operational and capital structure related cash flows.

It is interesting and, indeed, extremely informative, to identify the value drivers of a company. Focusing on these parameters enables sound financial strategies for value creation. To obtain the interrelationships between corporate value and the various value drivers, we concentrate our analysis on the FCF Model.

We define Free Cash Flows (FCF) as the cash flows (generated from operations) that are available for distribution to the full investor set of the company comprising of long term debt holders, equity holders and other non equity investors (e.g. preference stockholders, unfunded pension liabilities, operating leases, convertible debt, employee stock options etc.). FCF is, thus, the stream of cash flows generated from operations (after providing for taxation and meeting all the reinvestment needs of the company). Accordingly, FCF is independent of capital structure and is unaffected by any changes therein. Consistent with the above definition, we define "WACC" as the blended rate of return required by the company's entire investor set; "invested capital (IC)" as the aggregate investment, both in fixed and working capital (irrespective of sourcing) that is employed by the company to fund its operations (i.e. IC=Operating Assets –

Operating Liabilities); "net operating profit less adjusted taxes (NOPLAT)" as the total after tax income generated by the company's IC that is available for distribution to its investor set, (so that NOPLAT = EBIT – Taxes on EBIT where EBIT = PBT+ Interest Expense – Interest Income – Non-operating Income and Taxes on EBIT = Provision for tax +Tax shield on Interest Expense – Tax on Interest Income and Non-operating Income).

Thus,

$$FCF = NOPLAT - NI \tag{2}$$

where Net Investment (NI) is simply the incremental investment (net of depreciation) in operations related fixed and working capital during the year. Further, the "return on invested capital (ROIC)" is the amount of NOPLAT earned by the company per unit of its IC i.e

$$ROIC = NOPLAT/IC \tag{3}$$

and the growth rate (g) is:

$$g = \frac{Rev_t - Rev_{t-1}}{Rev_{t-1}} = \frac{NOPLAT_t - NOPLAT_{t-1}}{NOPLAT_{t-1}} = \frac{IC_t - IC_{t-1}}{IC_{t-1}} = \frac{NI_t}{IC_{t-1}} = IR \times ROIC \tag{4}$$

It is emphasized here that all the above terms are defined with the base as the company's operations. Hence, the FCF discounted value would be the value of the company's operations; non-operating assets need to be valued separately and added to the value of the company's operations to obtain the enterprise's FCF Model based value.

We have,

$$FCF = NOPLAT - NI = NOPLAT\left(1 - \frac{NI}{NOPLAT}\right)$$

$$= IC\frac{NOPLAT}{IC}\left(1 - \frac{NI/IC}{NOPLAT/IC}\right) = IC \times ROIC\left(1 - \frac{g}{ROIC}\right) \tag{5}$$

Assuming constant growth in revenues and consequential constant growth of FCFs (which will hold if the company reinvests the same proportion of its NOPLAT back into operations each year) as well as constant ROIC, we can value our company by the constant growth perpetuity model as:

$$V_{t=0} = \frac{FCF_{t=1}}{WACC - g} = IC_{t=0}\frac{ROIC - g}{WACC - g} \tag{6}$$

Whence the drivers of value are identified as:

(a) Return on Invested Capital and;
(b) Growth Rate

We, further have

$$\frac{\partial V_{t=0}}{\partial(ROIC)}=\frac{IC_{t=0}}{WACC-g} \tag{7}$$

and

$$\frac{\partial V_{t=0}}{\partial g}=IC_{t=0}\frac{ROIC-WACC}{(WACC-g)^2} \tag{8}$$

that lead us to the following conclusions:

(a) any increase in ROIC will lead to value enhancement, irrespective of the level of growth;

(b) for companies having $ROIC > WACC$, increase in growth rate is accompanied by value enhancement, with the rate of value enhancement increasing with the increase in the rate of growth rate, while companies with $ROIC < WACC$ lose value with increase in growth rate;

(c) however, in some cases, particularly for young business ventures, even if they have $ROIC < WACC$ initially, it is likely that increase in growth rate may naturally lead to enhanced ROIC and hence, result in value creation at some point. Mature companies with $ROIC < WACC$, on the other hand, are unlikely to exhibit this phenomenon – they would probably be working on an inappropriate business model or be the constituent of an unattractive industry.

Thus, it is the interplay between the growth rate, ROIC and WACC that lead to the creation of value. To elucidate this interrelationship, we consider two companies A Ltd. & B Ltd. with identical IC under varying set of assumptions:

Case 1

Let the WACC and growth rates of revenues and earnings of both A Ltd. and B Ltd. be identical while $ROIC_A > ROIC_B$. Since, $ROIC_A > ROIC_B$, it follows that to generate the same growth in earnings, lesser reinvestment of cash would be required by company A Ltd. than B Ltd. Thus, more cash would be liberated by company A Ltd. for distribution to its investors i.e. $FCF_A > FCF_B$. With $WACC_A = WACC_B$, $g_A = g_B$, it immediately follows that $V_A > V_B$.

Case 2

Now let $ROIC_A = ROIC_B$, $g_A = g_B$ and $WACC_A < WACC_B$. Since, $WACC_A < WACC_B$, it follows that company A Ltd. will distribute lesser cash to its investor set than company B Ltd. It will, therefore, have more funds available for investment back into the business. Now, because $ROIC_A = ROIC_B$, it follows that A Ltd. will generate more FCF than B Ltd. whence $V_A > V_B$.

Case 3

Now let $ROIC_A = ROIC_B$, $g_A > g_B$ and $WACC_A = WACC_B$. This is covered in clause (b) above. If $ROIC_A = ROIC_B = ROIC > WACC_A = WACC_B = WACC$, $g_A > g_B$ mandates

$$V_A = IC\frac{ROIC-g_A}{WACC-g_A} > IC\frac{ROIC-g_B}{WACC-g_B} = V_B \tag{9}$$

The converse of the above also holds.

Actually, the FCF Model has very sound theoretical underpinnings. Companies generate "value" for their investors by investing in resources en presenti in anticipation of greater cash flows in the future. The difference between the anticipated future cash inflows duly adjusted for time value of money and the level of risk associated with this stream (factored into the analysis by "discounting" these cash inflows at the appropriate risk adjusted rate" termed "cost of capital") and the investments (cash outflows) represent the "value created" by the company for its investor set. In other words, "value" created by a company is the present value of the surplus cash that remains after the company pays out the required returns to its investor set.

Not only has it a sound theoretical backing, FCF also emerges as a sound quantitative measure of value. To see this, we use the definition of FCF of eq. (5). so that we have

$$FCF = NOPLAT - NI = EBIT - Taxes\ on\ EBIT - NI$$
$$= EBIT - Provision\ for\ taxation - Interest\ tax\ shield - NI$$
$$= EBIT - Provision\ for\ taxation - I \times T_m - NI$$
$$= CF_e + I - I \times T_m - D \times g = E \times k_e + D \times k_d \left(1 - T_m\right) - \left(D + E\right) \times g = V\left(WACC - g\right) \quad (10)$$

whence $V = \dfrac{FCF}{WACC - g}$; where we have used the following:

(i) the cash flow to equity, $\left(CF_e\right)$, is the cash flow available for equity shareholders given by $CF_e = EBIT - I - Provision\ for\ taxation - NI + \delta D$;

(ii) the change in debt equals $\delta D = D \times g$ on the premise that, if FCF are growing at the constant growth rate, g, then the value of the firm also grows at the same value. If the debt-value ratio is assumed constant, this mandates that the debt will also grow at the same rate g.

(iii) the interest cost $I = D \times i = D \times k_d$ on the assumption that the market value of debt equals its face value whence, the coupon rate i equals the cost of debt k_d.

(iv) the value of equity $E = \dfrac{CF_e}{k_e - g}$, in view of assumption (ii) and assuming the validity of the constant growth perpetuity model;

(v) the value of the enterprise is the sum of the market values of its debt and equity i.e. $V = D + E$.

III. FCF Model and Equity Valuation

While the ECF Model (discounting equity cash flows at the cost of equity) enables the direct ascertainment of the intrinsic worth of the company's equity, it has the flaw of the cash flows mixing the operational and financial performance i.e. the equity cash flows (being the residual cash flows after meeting all operational and reinvestment needs and setting off all debt and non-equity claims), have the capital structure embedded in them. Thus, these cash flows are affected by the capital structure of the company.

An alternative method to arrive at the company's equity value, that has greater consistency, is to ascertain the value of the enterprise using the company's FCFs (that are independent of capital structure, being pre-interest cash flows) discounted at WACC and then deduct therefrom the value of the company's debt and other non-equity claims.

It is important to emphasize here once again that the discounting of FCF at WACC would give us the value of the company's operations (and not the total value of the company). We need to add thereto the value of the company's non-operating assets (net of such liabilities) to arrive at the company's value. It is desirable to value the non- operating assets (e.g. excess marketable securities, equity investments outside the business, non-consolidated subsidiaries etc.) separately because of the sheer heterogeneity of such assets – while some of them may be amenable to cash flow based valuation, others may be appropriately valued on assets e.g. replacement cost basis and still others may require valuation using some option pricing model. Aggregating the cash flows from such assets upfront with the company's operating FCFs would naturally lead to unfathomable distortion and discrepancy.

IV. Equivalence of FCF and APV Models

The APV Model assumes relevance when the constituent cash flows relevant for valuation differ significantly in terms of their risk profile. APV, then, envisages the separate discounting of each of these constituent cash flows at the appropriate risk adjusted rate and thereafter aggregating the present values so obtained to arrive at the company's value. In most cases, the cash flows that manifest themselves with significantly different risk profiles from the operational FCFs are the Interest Tax Shield (ITS) related cash flows because these cash flows are dependent on several strongly exogenous factors e.g. the company's expected ability to earn profits and thus, physically realize the shields, the treatment (carry forward and subsequent absorption) of business and other losses under the relevant tax laws, interest rates and tax rates for the future etc. The APV, in such situations, segregates the valuation process of the company's operations into two distinct components:

(a) the valuation of the company's operations as if it was financed by equity alone and;

(b) the valuation of all capital structure related costs and benefits e.g. ITS, issue costs, bankruptcy and distress costs etc.

It can be shown that under certain strong assumptions, the valuation by the APV method coincides with the FCF valuation. While the common assumptions of constant growth rate of cash flows, constant debt-equity ratio have been alluded to in the preceding sections, the cardinal assumption forming the premise of this analysis is that the tax shields have a risk profile analogous to the company's operating assets whence, they would, together with the company's FCFs, be discounted at the unlevered cost of equity $k_u = \dfrac{D \times k_d + E \times k_e}{D+E}$. We, then, have

$$V_{APV} = \frac{FCF + ITS}{k_u - g} = \frac{(D+E)\times(WACC - g) + D\times k_d \times T_m}{k_u - g}$$
$$= \frac{\left[D\times k_d \times (1-T_m) + E\times k_e - (D+E)\times g\right] + D\times k_d\times T_m}{k_u - g}$$
$$= \frac{D\times k_d + E\times k_e - (D+E)\times g}{k_u - g} = D + E = V \qquad (11)$$

It is necessary to reiterate here that we have assumed that the ITS have a risk profile that is identical to the company's operating assets and hence the resulting cash flows have been discounted at the company's unlevered cost of equity. Such a situation subsists if the company's debt grows in tandem with the company's business and hence, the company's value whence the interest cost and related tax shields will move in line with the company's operating assets. This may, however, not always be true and, in some cases, it may be appropriate to use the cost of debt for discounting these tax shield related cash flows e.g. when the company is likely to make structural changes in its financing in future leading to changes in the debt-equity ratio or the company's expected performance is likely to lead to major changes in market value of its debt and equity by significantly different proportions. This will, obviously, lead to a valuation that differs from the FCF valuation. The fallacy, in this case, lies in the fact that if the tax shields have a risk profile that differs from that of the operating assets, then the WACC will need to be adjusted to reflect this aspect whence we will end up with the same valuation as the FCF valuation. There may be situations, where it is appropriate to discount the ITS initially at the cost of debt for a few years and thereafter at the unlevered cost of equity. For instance, ITS for companies having heavy debt should be valued by discounting them at k_d so long as the debt remains massive. However, such companies would, in the normal course start retiring debt from their cash generation, if circumstances so permit, until an optimal debt-equity ratio is achieved whereafter this optimal ratio would be sustained and debt would grow only in tandem with the company's value. ITS for this period should, obviously, be valued at k_u. Continuing in the vein of the above exposition, it is instructive to examine the effect of replacing equity by debt in a company's financing mix. In a world of no taxes, this would have no effect on either the company's operational cash flows or the risk profile thereof. Hence, in the absence of taxes, the company's valuation would not change. As a corollary to this, the company's WACC would also remain unaltered with the change in weights being compensated by a corresponding reverse change in cost of equity. Obviously, an increase in debt results in an increase in the risk of equity related cash flows (debt enjoys preemptive right of payment of interest and repayment of principal over equity) whence the cost of equity would increase. This is, in essence, the Modigliani Miller proposition which postulates that valuation of a company is independent of its capital structure. Besides, even the interest rate, bankruptcy costs and distress costs would increase with incremental debt. However, if taxes on income prevail, substitution of equity by debt reduces payable taxes on account of ITS, whence cash flows and hence, value of the company will also increase. However, even this may not hold beyond a certain level of debt whence incremental costs of borrowing, bankruptcy costs and the costs of equity may, together, exceed the benefits of tax shields.

V. Equivalence of FCF and CCF Models

CCF is defined as the aggregate of the company's FCF and its capital structure related cash flows like ITS, issue expenses and bankruptcy/distress costs. The CCF Model envisages the valuation of a company by discounting the CCFs at the unlevered cost of equity. The equivalence of the CCF valuation with the traditional FCF valuation follows immediately from the results of Section 4 supra.

VI. Equivalence of FCF and ECF Models

Each of the above cash flow models arrive at the value of the company's equity shares by first valuing the company as a whole and thereafter deducting therefrom the value of debt and other non-equity claims. In contrast, the ECF Model directly arrives at the value of the company's equity by discounting the company's equity related cash flows at the company's levered cost of equity. For the purpose, we compute ECF by adding back noncash expenses and any increases in debt/other non-equity claims to the Net Income figure of the Income Statement and subtracting therefrom any incremental investments in fixed and working capital and nonoperating assets. The computation of ECF needs no adjustments for capitalized operating leases, debt or nonoperating assets since they are embedded in the company's ECF. Importantly, however, if the company's capital structure is expected to change over time, the corresponding cost of equity must be adjusted commensurate with the leverage expected.
As mentioned earlier, the FCF Model is compatible with the segment/business unit wise valuation of a company, by aggregating the respective values thereof. This happens to be the major shortcoming of the ECF Model. The ECF Model requires the allocation of debt and interest expense to each segment/business unit, if segment/unit wise valuation is desired, which is a fallacious task because of the absence of a sound basis for such allocation.

To establish equivalence between the FCF and ECF Models, we proceed as follows:

$$E=\frac{FCF}{WACC-g}-D=\frac{\left[CF_e+k_d\left(1-T\right)D-gD\right]\left(D+E\right)}{k_d\left(1-T\right)D+k_eE-g\left(D+E\right)}-D=\frac{CF_e\left(D+E\right)+\left[k_d\left(1-T\right)-k_e\right]DE}{k_d\left(1-T\right)D+k_eE-g\left(D+E\right)}$$

or $k_d\left(1-T\right)DE+k_eE^2-g\left(D+E\right)E=CF_e\left(D+E\right)+\left[k_d\left(1-T\right)-k_e\right]DE$ whence

$$E=\frac{CF_e}{k_e-g}=E_{ECF} \qquad (12)$$

VII. Treatment of tax shields

The issue of the present value of ITS is far from settled as of today. Not only is the appropriate discount rate for valuing these shields open to serious debate among academicians, but also the very issue of assigning a value to these shields has been questioned. In an extension of the Miller-Modigliani proposition, Miller (Miller, 1977) has stated that "I argue that even in a world in which interest payments are fully deductible in computing corporate income taxes, the value of the firm, in equilibrium, will still be independent of its capital structure". On the other extreme, the same author, in an earlier work, in co-authorship with Modigliani (Modigliani & Miller, 1958) has attributed a value to these tax shields (for perpetuity) by discounting the tax savings due to interest payments at the riskfree rate. Myers (Myers, 1974) prefers the discount rate to be reflective of the cost of debt on the premises that the tax savings due to interest payments on debt have the same risk profile as the parent debt. Contrary to this, discounting of tax shields is advocated at the unlevered cost of equity by Harris & Pringle (Harris & Pringle, 1985). The rationale is that such tax shields have the same systematic risk as the firm's operational cash flows.
In view of the immense importance of this issue, we illustrate the commonly practiced methods of the treatment of ITS by a numerical example. To keep the exposition simple, we consider a 3 year project costing 200 units financed equally by equity (requiring a return of 18%) and 10% (pre-tax) debt. EBDIT for the three years is assumed at 100, 150 and 300 units. Corresponding

depreciation and incremental gross investments in operations for each of the three years are assumed at 10 and 20 units respectively. A uniform tax rate of 40% is also postulated.

Method A – The FCF Model – Factoring ITS in the WACC

This method factors the ITS in the analysis by incorporating its effect through the use of post tax cost of debt in computing the WACC. The WACC, thus, works out to 12%. The FCF are calculated as EBIT (=EBDIT – Depreciation) – Taxes on EBIT + Depreciation – Incremental Gross Investment yielding 44, 74 and 164 units respectively for the three years. The discounted value of this cash flow stream @ 12% is 215.01 units.

Method B – The APV Model – Discounting ITS independently of the FCFs.

As mentioned above, the ITS are evaluated independently of the FCFs. The FCFs are discounted at the unlevered cost of equity (assuming the company to be completely equity financed) while the debt related ITS are discounted either at (i) the unlevered cost of equity; (ii) the cost of debt; or (iii) such other rate as is considered appropriate for the risk profile of the ITS. In this problem the unlevered cost of equity is 14%. The FCFs have been worked out earlier at 44, 74, 164 respectively and the ITS are 4 units for each year.

The value of the discounted FCFs at 14% is 206.23 while that of the ITS at the unlevered cost of equity (14%) is 9.28 leading to an aggregate valuation of 215.52. On the other hand, if the ITS are discounted at the cost of debt (10%) the aggregate valuation becomes 216.18. However, it is believed that the cost of equity needs adjustment to reflect the risk profile of the ITS and hence, we end up with a valuation equal to that by the earlier method.

VIII. On the unlevering of the cost of equity

Several cash flow based valuation models e.g. the APV Model, CCF Model involve discounting the appropriate cash flows at the unlevered cost of equity k_u. It is, therefore, necessary for the completeness of this article to outline the process of unlevering/levering the cost of equity. The process has its genesis in the much celebrated Modigliani-Miller (MM) "capital structure irrelevance" propositions of corporate finance. The principles essentially mandate that, in a world of no taxes on income, the value of a company and hence, its cost of capital, is independent of the company's capital structure. However, MM do accept that, in the presence of taxes on income, value addition may be achieved by replacing equity by debt on account of the deductibility of interest in computing taxable income as a revenue expense under the taxation laws and the consequential tax shields.

To establish their contention, they consider two firms U Ltd. and L Ltd. that are operationally identical (and so are expected to generate the same EBIT at every point in time) but differ in terms of their capital structure with U Ltd. being unlevered (i.e. entirely equity financed) and L Ltd. being levered with a debt of D_l besides its equity of E_l so that we have $V_u = E_u$ and $V_l = D_l + E_l$. Further, let T_C, T_{PD}, T_{PE} be the respective tax rates on corporate income, personal income by way of interest and personal income by way of equity earnings (e.g. dividends and capital gains). It, then, follows that the post tax income available to the debt holders of L Ltd. is $I(1-T_{PD})$, the post tax income for the equity shareholders of U Ltd. is $EBIT(1-T_C)(1-T_{PE})$ while that for the equity shareholders of L Ltd. is $(EBIT-I)(1-T_C)(1-T_{PE})$. Thus, the post tax income available to the entire investor set of U Ltd. (comprising of only equity shareholders E_u)

is $EBIT(1-T_C)(1-T_{PE})$ while that for the investor set of L Ltd. (comprising of debtholders D_l and shareholders E_l) is $EBIT(1-T_C)(1-T_{PE})+I(1-T_{PD})\left[1-\frac{(1-T_C)(1-T_{PE})}{(1-T_{PD})}\right]$ whence the value created by the introduction of debt is the present value of $ITS=I(1-T_{PD})\left[1-\frac{(1-T_C)(1-T_{PE})}{(1-T_{PD})}\right]$. In the special case when the debt is constant, perpetual and quoted at face value, $I=k_dD_l$ and the present value of ITS can be worked out as a constant perpetuity using the discount rate $k_d(1-T_{PD})$ (since $I=k_d(1-T_{PD})D_l$ is the post-tax income for the debt holders) so that $V_{tax}=PV(ITS)=D_l(1-T_{PD})\left[1-\frac{(1-T_C)(1-T_{PE})}{(1-T_{PD})}\right]$. Therefore, MM postulate that there would be value addition for the company if $T_C(1-T_{PE})>T_{PD}-T_{PE}$.

There are two important corollaries to the above proposition viz.

(a) The market value of the firm's economic assets is equal to the market value of the financial claims against those assets i.e.

$$V_u+V_{tax}=D+E \tag{13}$$

where V_u, V_{tax}, D, E are respectively the market value of the unlevered firm i.e. the market value of the firm's assets (other than ITS), the value of the ITS, the market value of debt raised by the company and market value of its equity.

(b) The total risk of the firm's economic assets, both operating and financial, must equal the financial claims against those assets.

Since, the cost of capital is a measure of the risk profile of the firm, this proposition translates to:

$$\frac{V_u}{V_u+V_{tax}}k_u+\frac{V_{tax}}{V_u+V_{tax}}k_{tax}=\frac{D}{D+E}k_d+\frac{E}{D+E}k_e. \tag{14}$$

Since, $V_u+V_{tax}=D+E$, we have

$$k_u=\frac{1}{V_u}(Dk_d+Ek_e-V_{tax}k_{tax}) \tag{15}$$

The proof of both these propositions follows from arbitrage arguments similar to those proving the main proposition. If we have two firms having the same operating characteristics and the same market value of their economic assets but differing in the aggregate market value of their respective financial claims (debt and equity), arbitrage profits by way of accretion in income could be realized by selling off one's investments in the company having the higher value of debt and equity and investing the proceeds in the company having the lower value of its aggregate of debt and equity together with borrowing/lending of an amount that ensures that the investor's risk profile (as measured by the debt-equity ratio) remains unaltered as a result of this arbitrage transaction. To establish the proof explicitly, we consider two firms U Ltd. and L Ltd. that are operationally identical but differ in terms of their capital structure with U Ltd. being unlevered and L Ltd. being levered with a debt of D_l besides its equity of E_l. Let us assume that the value of the economic assets of both the firms is the same but the aggregate market values of the respective claims differs i.e. $E_u \neq D_l + E_l$. Let, if possible $E_u < D_l + E_l$. Let an investor X own x fraction of the shareholding of L Ltd. whence his income from this investment is $x(EBIT - I)$. To perform the arbitrage process, X sells off his shareholding in L Ltd. to realize cash worth xE_l, borrows a sum of xD_l on his personal account (on exactly the same terms and conditions as the debt of L Ltd. – so that his personal debt equity ratio and hence, his risk profile remains completely unchanged). He invests these resources $x(D_l + E_l)$ in buying the equity of U Ltd. to get $x\frac{(D_l + E_l)}{E_u}$ fraction of the company's shares. His income from this shareholding will now be $EBIT \times x\frac{(D_l + E_l)}{E_u}$ while the interest that he will pay on his personal borrowings will be $\frac{I}{D_l} \times xD_l = xI$, $\frac{I}{D_l}$ being the rate of interest on the borrowings (that is assumed equal to the rate of interest on corporate borrowings). Thus, the net income of X after the arbitrage transactions would be $x\left[EBIT\frac{(D_l + E_l)}{E_u} - I\right]$ resulting in an accretion of income (since $E_u < D_l + E_l$). Non-sustainability of arbitrage in equilibrium thus mandates that $E_u = D_l + E_l$, thereby establishing the corollary.

There are three special cases in which the expression for k_u takes particularly simple forms:

(i) If debt grows as a constant proportion of enterprise value, the risk of realization of the tax shields mirrors the operating risk so that $k_{tax} = k_u$ whence

$$k_u = \frac{D}{D+E}k_d + \frac{E}{D+E}k_e. \tag{16}$$

It is pertinent to emphasize here that the unlevered cost of equity here depends on the leverage ratio. This is because MM accept the fact that value is created by incorporating debt into the capital structure because of the ITS. The quantum of value accretion due to ITS obviously depends on the leverage employed. Further, the enterprise value is defined as the cumulative value of the unlevered firm and the present value of the ITS.

(ii) If the market debt- equity ratio is expected not to remain constant then the value of ITS will be more appropriately valued in relation to the forecasted debt rather than the operating assets so that the risk of realization of the ITS will mirror the risk of debt and $k_{tax} = k_d$. For instance, a company that is not doing well and is unable to earn sufficient profits to realize the ITS will also have increased risk of default on its debt leading to a fall in the value of debt. Under this assumption,

$$k_u = \frac{D - V_{tax}}{D + E - V_{tax}} k_d + \frac{E - V_{tax}}{D + E - V_{tax}} k_e \tag{17}$$

(iii) If (ii) holds i.e. $k_{tax} = k_d$ and further, the monetary value of debt is constant and the debt is perpetual and quoted at face value, then we can calculate the present value of the ITS as a constant perpetuity, so that $V_{tax} = \frac{IT_m}{k_d} = \frac{k_d DT_m}{k_d} = DT_m$ whence

$$k_u = \frac{D(1-T_m)}{D(1-T_m)+E} k_d + \frac{E(1-T_m)}{D(1-T_m)+E} k_e \tag{18}$$

IX. Enterprise Economic Profit (EP) Model

A serious criticism of the FCF Model is that the FCFs do not link to the company's economic performance. For instance, declining FCFs need not necessarily signal a declining operational performance; such a situation can also relate to significant reinvestments into capital assets for promoting future growth. Although, as we establish in the sequel, the EP Model and FCF Model result in identical valuations under certain conditions, the former is more explicit in highlighting value creation by the company. EP focuses on the differential return between ROIC and WACC. We define "Economic Profit" as:

$$EP_t = IC_{t-1}\left(ROIC - WACC\right) \tag{19}$$

whence, we have, by using eq. (6):

$$V_{t=0} = IC_{t=0} + IC_{t=0}\frac{ROIC - WACC}{WACC - g} = IC_{t=0} + \frac{EP_{t=1}}{WACC - g} \tag{20}$$

To establish equivalence between the FCF and EP Models, we proceed as follows:

$$V_{t=0} = \sum_{t=1}^{\infty}\frac{FCF_t}{(1+WACC)^t} = IC_{t=0} + \sum_{t=1}^{\infty}\frac{IC_t}{(1+WACC)^t} - \sum_{t=0}^{\infty}\frac{IC_t(1+WACC)}{(1+WACC)^{t+1}} + \sum_{t=1}^{\infty}\frac{FCF_t}{(1+WACC)^t}$$

$$= IC_{t=0} + \sum_{t=1}^{\infty}\frac{IC_t}{(1+WACC)^t} - \sum_{t=1}^{\infty}\frac{IC_{t-1}(1+WACC)}{(1+WACC)^t} + \sum_{t=1}^{\infty}\frac{FCF_t}{(1+WACC)^t}$$

$$= IC_{t=0} + \sum_{t=1}^{\infty} \frac{\left[IC_t - IC_{t-1}(1+WACC)\right] + \left[NOPLAT_t - (IC_t - IC_{t-1})\right]}{(1+WACC)^t}$$

$$= IC_{t=0} + \sum_{t=1}^{\infty} \frac{NOPLAT_t - WACC \times IC_{t-1}}{(1+WACC)^t} = IC_{t=0} + \sum_{t=1}^{\infty} \frac{EP_t}{(1+WACC)^t} \quad (21)$$

It follows from the above that the value of a company's operations equals the book value of its initial invested capital plus the present value of its future economic profits discounted at the WACC. In the foregoing, equivalence has been established on the following premises viz.

(i) beginning of the year invested capital has been used to calculate economic profit of each year;
(ii) consistency in the method of calculation of invested capital for calculating ROIC and economic profit;
(iii) constant cost of capital.

X. Residual Income (RI) & Corporate Valuation

Valuation by the RI Model mandates that the value of a company is equal to the value of its initial equity capital E(0) plus the present value of the RI discounted at the levered cost of equity. For the purpose, we define RI of an year as net income for the year less a return on the beginning year's equity balance at a rate equal to the levered cost of equity

$$RI(t) = I(t) - k_e E(t-1) \quad (22)$$

In an ideal setting, the RI and the "Dividend Discount (DD)" Model to valuation converge to the same figure so long as we adhere to the "clear surplus relation" i.e. that net income less net dividends account completely for the change in shareholders' equity so that

$$I(t) - D(t) = E(t) - E(t-1) \quad (23)$$

The equivalence between the DD Model and the RI Model can be easily established by mathematical induction. We have,

$$E(0) + \frac{RI(1)}{1+k_e} = E(0) + \frac{I(1) - k_e E(0)}{1+k_e} = \frac{E(0) + I(1)}{1+k_e} = \frac{E(1) + D(1)}{1+k_e} \quad (24),$$

$$E(0) + \frac{RI(1)}{1+k_e} + \frac{RI(2)}{(1+k_e)^2} = E(0) + \frac{I(1) - k_e E(0)}{1+k_e} + \frac{I(2) - k_e E(1)}{(1+k_e)^2}$$

$$= \frac{D(1)}{1+k_e} + \frac{D(2) + E(2)}{(1+k_e)^2}$$

(25)

Let us assume that

$$E(0)+\frac{RI(1)}{1+k_e}+\ldots+\frac{RI(k)}{(1+k_e)^k}=\frac{D(1)}{1+k_e}+\ldots+\frac{D(k)+E(k)}{(1+k_e)^k} \tag{26}$$

then

$$E(0)+\frac{RI(1)}{1+k_e}+\ldots+\frac{RI(k)}{(1+k_e)^k}+\frac{RI(k+1)}{(1+k_e)^{k+1}}=\frac{D(1)}{1+k_e}+\ldots+\frac{D(k)+E(k)}{(1+k_e)^k}+\frac{RI(k+1)}{(1+k_e)^{k+1}}$$

$$=\frac{D(1)}{1+k_e}+\ldots+\frac{D(k)+E(k)}{(1+k_e)^k}+\frac{I(k+1)-k_eE(k)}{(1+k_e)^{k+1}}=\frac{D(1)}{1+k_e}+\ldots+\frac{D(k)}{(1+k_e)^k}+\frac{I(k+1)+E(k)}{(1+k_e)^{k+1}}$$

$$=\frac{D(1)}{1+k_e}+\ldots+\frac{D(k)}{(1+k_e)^k}+\frac{D(k+1)+E(k+1)}{(1+k_e)^{k+1}} \tag{27}$$

so that the identity

$$E(0)+\frac{RI(1)}{1+k_e}+\ldots+\frac{RI(k)}{(1+k_e)^k}=\frac{D(1)}{1+k_e}+\ldots+\frac{D(k)+E(k)}{(1+k_e)^k} \tag{28}$$

holds for all positive integers k. Now, if we extend this summation over the entire life of the firm, the final value of $E(k)$ must necessarily be zero since whatever surplus remains for the equity shareholders on liquidation would be distributed to them as the equivalent of final dividend. In other words, if we sum the above series over the entire life of the firm, we must have

$$E(0)+\frac{RI(1)}{1+k_e}+\ldots+\frac{RI(n)}{(1+k_e)^n}=\frac{D(1)}{1+k_e}+\ldots+\frac{D(n)}{(1+k_e)^n} \tag{28}$$

thereby establishing the equivalence of the two approaches. However, it is considered impracticable to project out the stream of dividends or residual income over the entire life of the firm and usually, in valuing firms, one makes explicit forecasts for a certain number of years and thereafter uses a steady state growth model for computing a terminal value assuming an appropriate steady state growth rate of an infinite stream of dividend flows/residual income i.e.

$$P=\sum_{i=1}^{n}\frac{D(i)}{(1+k_e)^i}+\frac{D(n+1)}{(1+k_e)^n(k_e-g)} \tag{29}$$

or

$$P=E(0)+\sum_{i=1}^{n}\frac{RI(i)}{(1+k_e)^i}+\frac{RI(n+1)}{(1+k_e)^n(k_e-g)} \tag{30}$$

where $D(n+1)=D(n)(1+g)$ & $RI(n+1)=RI(n)(1+g)$. (31)

In such a case, we need to exercise care in computing $D(n+1), RI(n+1)$ to ensure equality of the two approaches. Let g be the steady state growth rate of income as well as equity so that

$$D(n+1) = E(n) - E(n+1) + I(n+1) = E(n) - (1+g)\left[E(n) - I(n)\right] \qquad (32).$$

Therefore

$$\sum_{i=1}^{n} \frac{D(i)}{(1+k_e)^i} + \frac{D(n+1)}{(1+k_e)^n (k_e - g_{dividend})} = E(0) + \sum_{i=1}^{n} \frac{RI(i)}{(1+k_e)^i} - \frac{E(n)}{(1+k_e)^n} + \frac{D(n+1)}{(1+k_e)^n (k_e - g_{dividend})}$$
$$= E(0) + \sum_{i=1}^{n} \frac{RI(i)}{(1+k_e)^i} - \frac{E(n)}{(1+k_e)^n} + \frac{E(n) - (1+g)\left[E(n) - I(n)\right]}{(1+k_e)^n (k_e - g)}$$
$$= E(0) + \sum_{i=1}^{n} \frac{RI(i)}{(1+k_e)^i} - \frac{E(n)}{(1+k_e)^n} + \frac{(1+g)I(n) - gE(n)}{(1+k_e)^n (k_e - g)}$$
$$= E(0) + \sum_{i=1}^{n} \frac{RI(i)}{(1+k_e)^i} - \frac{E(n)}{(1+k_e)^n} + \frac{(1+g)I(n) - k_e E(n) + (k_e - g)E(n)}{(1+k_e)^n (k_e - g)}$$
$$= E(0) + \sum_{i=1}^{n} \frac{RI(i)}{(1+k_e)^i} + \frac{(1+g)I(n) - k_e E(n)}{(1+k_e)^n (k_e - g)} = E(0) + \sum_{i=1}^{n} \frac{RI(i)}{(1+k_e)^i} + \frac{RI(n+1)}{(1+k_e)^n (k_e - g)}$$

(33).

thus, establishing equality of the two approaches once again. What needs to be noted, however, in the above is that, unlike the usual practice, $D(n+1) \neq D(n)(1+g)$ and $RI(n+1) \neq RI(n)(1+g)$.

It, therefore, follows that the very existence of these differing schemes is mandated more by practical considerations than the underlying philosophy viz. that the enterprise value is the aggregate present value of the entire stream of dividends emanating from the enterprise discounted at the cost of equity. The fact, then, that these methods do, in practice, yield varying outcomes leads us to question the implementation methodology rather than the theoretical premises.

XI. Multipliers & Valuation – P/E Ratio & Leverage

Use of Price –Earnings or other similar multiples of analogous companies for the corporate valuation envisaged are becoming increasingly popular probably because of their perceived simplicity e.g. one develops one's own estimate of the EPS on a set of premises and multiplies it with the P/E multiple averaged over a set of similar companies to arrive at a value of the company's share. However, such use of multipliers comes with several caveats e.g.

(a) The choice of multiples must be consistent with the underlying earnings stream that one is attempting to capitalize. For instance, the P/E ratio relates the value of equity to the income stream available to the equity shareholders i.e. profit after tax and preference dividend. It is clearly unsuitable for an exercise which envisages the valuation of a corporate on the free cash flow model. In such a scenario, it would be more desirable to use a multiple based on EBDIT.

(b) A very serious impediment to the use of income based multipliers is that such multipliers are dependent on accounting policies pursued by the relevant corporate e.g. adoption of different methods of depreciation, amortizations of intangibles and their valuations, accounting for foreign exchange transactions and similar accounting issues for which dichotomous or even polychotomous treatment is enabled by the accounting regulators.

(c) Such multipliers are also subject to misevaluations by the markets due to short term aberrations, information asymmetries etc.

(d) There are also a number of computational constraints that limit the use of multipliers for valuation e.g. identifying corporates of similar operational and financing dimensions, existence of similar timing conventions for accounting periods etc.

Under certain assumptions and in a world of no taxes, it is possible to arrive at a functional relationship between leverage and the Price-Earnings Multiple. To derive this expression, we start by considering an unlevered (all-equity financed) company with an equity capital that is valued by the market at E_u. Since the company has no debt, its market value will equal the market value of its equity so that $V = E_u$. On account of the same reason, the company's Net Income (NI) will equal its NOPLAT. whence we have

$$(P/E)_u = \frac{E_u}{NI_u} = \frac{V_u}{NOPLAT_u} \tag{34}$$

Now, if an amount D of perpetual debt is introduced into the company and this debt is traded at face value, then,

$$NI = NOPLAT - I = NOPLAT - k_d D = NOPLAT - k_d\left(\frac{D}{V}\right)V$$

$$= NOPLAT\left[1 - k_d\left(\frac{D}{V}\right)(P/E)_u\right] \tag{35}$$

and

$$E = V - D = NOPLAT \times (P/E)_u \times \left(1 - \frac{D}{V}\right) \tag{36}$$

whence

$$(P/E) = (E/NI) = \frac{(P/E)_u \times \left(1 - \frac{D}{V}\right)}{1 - k_d\left(\frac{D}{V}\right)(P/E)_u} = \frac{1}{k_d} + \frac{\frac{1}{k_d} - (P/E)_u}{k_d\left(\frac{D}{V}\right)(P/E)_u - 1} \tag{37}$$

In today's environment, it is not uncommon to encounter valuation of financial entities or products that have a complex structure of cash flows e.g. projects may have embedded abandonment options, fixed income securities may possess callable or puttable options, convertible shares and/or warrants are, obviously, very well known. In such cases of valuation, one needs to take care of these singular characteristics and ascribe an appropriate figure to the value addition generated there from. A possible approach to this value imputation could be through the use of Black-Scholes option price formula or variants thereof. It needs to be emphasized that all pricing models for contingent claims carry with them a bucket of rigid assumptions (e.g. the Black Scholes model imputes a lognormal distribution of the underlying asset price process) so that while adopting any such framework, one should necessarily test the valuation environment against these premises before proceeding with use of the model.

XII. Conclusion

In this article, we have espoused the cause of DCF valuation emphasizing its immense versatility – this method can be adapted to resolve most valuation problems. However, while the approach has sound underpinnings, its actual implementation warrants care and restraint. Some of the conscientious issues have been attended to in the preceding paragraphs. A deep examination would, nevertheless, reveal that most of the perceived shortcomings of the DCF methodology, in actual fact, owe their origin to faulty implementation and DCF, viewed in itself, makes strong financial sense. To reiterate, a "due diligence" on a DCF exercise needs to focus on the following facets:

(a) That inflation effects are duly incorporated in the analysis i.e. either real cash flows are discounted at real rates or nominal cash flows at nominal rates, we must ensure compatibility between the numerator & denominator;

(b) The discount rate should be adjusted only for the systematic (market) risk, diversifiable risk should carry no weightage insofar as projected returns are concerned;

(c) Appropriate treatment of taxation is paramount because, in most cases of valuation, only the after tax flows are relevant as they constitute the realizable cash flows for the providers of capital;

(d) Care should be taken to quantify all incremental costs and benefits, whether tangible or otherwise, those are related to or emanate from the asset to be valued;

(e) A related issue is the possible existence of special features embedded in the investment opportunity. A quantification of such attributes is mandatory for a correct application of DCF.

In view of the immense significance of issues of asset valuation in the contemporary environment, they are occupying centre stage across the globe with academicians and practitioners grappling with facts, figures, accounts and mathematics in efforts to achieve a precise valuation model. A school of these workers are attempting to juxtapose probabilistic concepts like expected cash flows together with the probability distribution thereof into the DCF formulation in an attempt to enhance its efficacy (Schumann, 2006). Variants of DCF in the domain of "fuzzy mathematics" have also been propounded (Huang, 2008). However, it still remains to be seen as to what extent "man can emulate reality".

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Assessing E-Banking in Nam Dinh, Viet Nam ─Adopting TAM Model

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Abstract

As Vietnam is booming and the society is opening up, E-commerce has been putting its first footstep in this rising economy. The past decade has seen Internet and E-commerce starting to positively tune into Vietnamese daily life. However, to really give the economy an upsurge, it is essential that the banking sector be reformed toward an E-age. E-banking could be the next step to do for the economy to really transform and productivity boosted. Like any other emerging economy, Vietnam has motivators and hindrance for such a platform to be implemented widely. In this research, we seek to find out what factors influences Banks' choice to adopt E-banking in Nam Dinh province. The research follows the Technology Acceptance Model (TAM). The research findings show that the perception of usefulness is the most important factor that determines whether or not banks would adopt E-banking. Following perceived usefulness, perceived ease of use would also positively influence banks' decision in further involvement with a new technology. These findings have induced numerous implications for policy makers, management and software developers.

Keywords: TAM model, Vietnam, Perceived usefulness, Perceived ease of use

I. Introduction

In the early years of the 21st century, E-commerce has spread to developing countries. The birth and growth of E-commerce in these developing economies is an inevitable trend in the process of globalization and digitization. E-banking, or Internet banking, is emerging as one of the prominent e-commerce trends in fast developing economies. The introduction of on-line banking services in Vietnam in the past two years has received enthusiastic responses. Ever since the State Bank of Vietnam initiated Inter-Bank Electronic Payment, the speed of electronic payment has been remarkably improved. In 2005, to total number of electronic banking transactions was 3.5 million. In 2006, this number increased to 6.3 million. According to Techcombank, its online banking has attracted 1,000 accounts just two weeks after launching the service. One third of the accounts have the balance of 50 million dong or higher (InfoTV, 2009), (Saigontimes, 2008).

Singapore, March 4, 2011 – comScore, Inc. (NASDAQ: SCOR), a leader in measuring the digital world, released the latest results from a study of Internet usage in Southeast Asia. The report found that an increasing number of consumers across the region turned to online banking throughout 2010. Across markets in Southeast Asia, visitation to online banking sites increased strongly in the past year, growing by double-digits percentages across all six countries measured. Vietnam is not left out of this global trend. Especially, the rising finance sector in Vietnam, with its increasing pressure to mature, is requiring a big digital boost to fulfill its potential.

From the point of view of a policy maker, it is crucial to understand the determinants of E-banking implementation given Vietnam's infrastructure and cultural context. This is a motivation for this research to look at ways to develop E-commerce applications for Vietnamese banks. It is also vital to learn what banks' management perceive as the most feasible E-banking applications at this point. This knowledge basically is a core-competency assessment to help us predict the direction of E-banking in Vietnam in the near future and possibly in the long run. It also reveals banks' current technology competence, and their current perception of E-banking service demand among customers, which is also a useful insight in designing well-suited and timely policies.

Online Banking Category Visitation by Market
January 2011 vs. January 2010
Total Audience, Age 15+ - Home & Work Locations*

	Total Unique Visitors (000)		
	Jan-10	Jan-11	% Change
Malaysia	2,360	2,746	16%
Hong Kong	1,304	1,543	18%
Vietnam	**701**	**949**	**35%**
Singapore	779	889	14%
Indonesia	435	749	72%
Philippines	377	525	39%

Source: comScore Media Metrix

To address this question, the world's scholarship have focused on using the Model of Technology Acceptance (TAM) as a framework to benchmark all discussions on what determines the level of acceptance of E-banking across organizations, sectors, and countries. The Model of Technology Acceptance was initially developed by Fred Davis in 1989, which explores the relationship between perceived usefulness, perceived ease of use and Actual usage in technology applications.

Based on the above background, current knowledge and current state of e-business application in Vietnam's banking industry, we propose the following research questions: (1) how does Perceived Ease of use influence Perceived Usefulness? (2) how does Perceived Ease of Use and Perceived Usefulness influence banks' attitude toward E-banking? (3) how does Perceived Usefulness and Banks' attitude toward E-banking influence Bank's intention to use E-banking?

II. Literature review

To study factors impact to user's acceptance about a particular technology, there are a lot of people adopted some of theories such as TRA, TBP or TAM model. The TAM model was developed by Davis 1989 aim to evaluate acceptance of individual people for a particular technology (Davis, 1989). The objective of this thesis is study acceptance of people who are staffs, managers working on banking field at Nam Dinh province. Therefore, the TAM model is suitable better for this propose of thesis. Moreover, in january-2000, there are 424 journals of many researchers who applied the TAM model in order to evaluate user's behavior intention (Venkatesh and Davis, 2000). Mean that the TAM model is a favor model to research user's acceptance for applying a particular technology. Therefore, this thesis will apply the TAM model aim to evaluate acceptance of user to use e-banking in the banking field at Nam Dinh - Vietnam.

II.1 What is E-commerce for banking?

The answer varies across researches. According to Daniel, Mols and Sathye, E-banking is the supply of a variety of services, which allow customer to have access to information and conduct retail banking services via computers, television or mobile phones (Lavin Aghaunor, 2006). Burr, 1996, on the other hand, defined E-banking in a more interactive manner compared to Daniel, Mols and Sathye's customer-centric approach. He describes E-banking as "an electronic connection between banks and customers" to manage and control financial transactions. In several contexts, E-banking can be understood as banking on a variety of platforms, such as:

Internet banking, Telephone banking or mobile banking, PC banking, or even Automatic Teller Machine (ATM) banking.

How we understand the concept of E-banking has an important implication for strategies and policies. Some managers only consider E-banking as an e-channel to speed up current transactions. Yet, E-banking could also entail the concept of Virtual bank, operating without human presence, which is far from the traditional brick and mortar institutions we have been so accustomed to (Yahya Dauda, Mphil, 2007). Virtual bank is a radical idea that could become an essential tool for banks' strategic market segmentation (Yahya Dauda, Mphil, 2007). This multi-dimensional nature of E-banking is exciting in the sense that it would provide new opportunities and challenges for banks that choose embrace such new ideas.

II.2 E-banking in Vietnam

Like Vietnam's banking sector, E-banking in Vietnam is also making baby steps toward modernization. The concept of E-banking in Vietnam to date only rests at computerization of al traditional banking activities. While most banks in Vietnam now have websites to communicate with their customers and to present their information, commercial banks are reluctant to adopt E-banking is the major instrument for growth. The standard format of bank identifier code, SWIFT, was introduced in Vietnam in March 2005. However, in 2007, only a few banks such as Vietcombank, Incombank, ACB, Exim Bank, ANZ and City Bank provided home banking. Vietcombank, Techcombank, HSBC, and ANZ and City bank offered telephone banking. Incombank, ACB, and Techcombank tiptoed around mobile-banking (Banks in Vietnam, 2007). Some banks like Citibank, HSBC, Deutsch Bank, ANZ bank started to provide real E-banking for the business sector.

Recent years, however, witnessed significant improvements in these areas. While Vietnam is still a cash economy, ATM transactions have become a daily experience for most Vietnamese. As of 2007, awareness of ATM cards, credit cards and debit cards were 91 percent, 21 percent and 8 percent respectively (Look at Vietnam, 2009). Visa was the most recognized payment cards. As reported by SBV, the total number of ATM cards issued in 2008 grew 100 percent compared to 2007. As of 2008, the total number of ATM cards issued was 4.2 million, and the number of ATM machines was 2, 257 (Wikipedia, Theory of reasoned Action). The story of E-payment systems seemed less intriguing compared to ATM banking. The reasons were probably lack of secured means of on-line payment. To overcome the high fraudulence rate of Internet banking, as early as 2009 did the State Bank of Vietnam introduce a new online payment system with advanced security protection of technology? The bank suffered from 37 million USD losses from banking fraud in the first six month of 2008. In early 2009, the bank launched this new centralized e-payment system, covering 1500 branches and 63 banks. The system performs 2 million transactions worth of 1.9 billion per day.

The issue of Internet banking security has become a thorny topic in many conferences on technologies and banking recently. A research conducted by BKIS Security Vietnam in 2010 at 20 biggest banks of Vietnam who have adopted E-banking on their web security level showed that security remained the biggest issue that prevent E-banking from thriving. In a conference on "Web security problems of E-banking in Vietnam", Mr. Nguyen Minh Duc, Director of BKIS Security revealed that all 20 surveyed banks have problems with their network security. These problems included: personnel, process, ICT network, transmission, central management platform and environment, and E-banking technology applications (Fred D. Davis, Perceived Usefulness, MIS Quarterly, 1989). These problems would pose great obstacles in smooth implementation of E-banking in Vietnam.

Mobile banking did not show very exciting signals either. As Internet banking moves slowly and cautiously forward, mobile banking in Vietnam has only made staggering baby steps. Main operators such as VNPT, Mobifone and Viettel have been making attempts to align with banks to build mobile payment systems that leveraged on their extensive pool of mobile customers. However, due to limited technology aptitude, these mobile payment systems remained modestly functional. Basically current mobile banking are SMS-based, a rather primitive way of access to bank resources and information. On top of that, the question of network security is still looming, making it hard to inject a big push in this segment of E-banking in Vietnam.

With a sizable pool of online and mobile population, Vietnam market holds great potential for E-banking. The high growth economy also needs speedy circulation of capital to meet up with its capacity. E-banking has only emerged as a phenomenon in Vietnam in the last 5 years, which explains its modest achievements and the country's caution in adopting it. Despite the zeal and exuberance of customers when first exposed to this high-end way of banking, the question o network security still hover over most E-banking plans and strategies.

II.4 E-banking in Nam Dinh

Nam Dinh is considered a highly potential economic zone in Vietnam with the average growth rate in the past five years reaching 7.7 percent. (Vvenkatesh.com, Theoretical Models) The percentage of manufacturing, construction and services is 61 percent. This signals a structural shift into a more production-oriented economy as opposed to a previously agricultural economy. Nam Dinh possesses some of the most developed textile and garment factories in the country, which has contributed significantly to the country's export quotas in the past five years. As the economy speeds up, the banking sector in Nam Dinh also has to follow to meet the rising capita needs among businesses. However, the growth of banking service sector in Nam Dinh has not been as robust. Part of the reason is the catching up IT infrastructure in Nam Dinh.

Another reason is that attention to E-banking has been mostly Hanoi and Ho Chi Minh city centric and other provinces would follow the trend. Lack of in-depth researches resulted in a less specific description of the big picture of E-banking adoption in Nam Dinh. Currently there are about 30 banks in Nam Dinh, with many of them being branches of big national banks. A large part of the remaining banks are targeted to support the poor in funding their livelihood activities. This very specific nature of banks might also influence the speed at which they adopt Internet banking because the demand for such high end services is still limited.

II.5 Technology Acceptance Model

In this study, we attempt to utilize the Technology Acceptance model to assess the determinants that affects Nam Dinh ban's decision to adopt E-commerce. The reason why we decided to choose this model as the analytical framework is because it's high level of relevance to the research questions and its wide applications within research literature on technology acceptance. Moreover, the TAM model is the most typical quantitative model to assess technology penetration. It is also evident that to have a detailed, accurate and quantifiable measurement of technology acceptance, it is highly important that quantitative approach is applied. First, it would be able to confirm numerically the accuracy of hypotheses. Second, it would be able to justify the strength of relationship between independent and dependent variables. As such, TAM model is a logical choice as anaylitical framework for this study.

Many studies sought to answer the question of what determine banks' acceptance of E-banking. Among others, the Technology Acceptance Model has earned wide and far influences and ramifications. The original version of TAM model was the Theory of Reasoned Action (TRA), developed by Ajzen and Fishbein (1980), which aimed at studying attitude and behavior. TRA is a general behavioral study which suggests that a person's attitude toward a behavior and social norms will affect how the person behaves later on (Kwasi Amoako – Gyampah and A.F. Salam, 2003). Based on this foundation, Fed Davis and Richard Bagozzi developed the Technology Acceptance Model (1989 &1992). The TAM model is more technology centric, where a lot of attitude measures have been replaced by two variables: ease of use and usefulness (Kimberly, J.R, & Evanisko, M.J., 1981). The study's instrument is a questionnaire using Linkert 5 point scale to measure respondent's attitude and behavior. In 2000, Venkatesh and Davis revised and extended the original TAM model to TAM 2. The TAM 2 model sought to examine perceived ease of use and perceived usefulness in light of social influences and behavioral intention. Specifically, the model included extra social influencers such as: Performance expectancy, effort expectancy, social influence, and facilitating conditions. Demographic attributes are also taken into account with gender, age, experience and voluntariness of use being the dependent variables (Tornatzky, L.G., & Fleischer, M., 1990).

Like TRA, TAM assumes that a person is free to act upon their intention without a barrier, which, to some extent is unrealistic in today's world. This explains multiple corresponding literatures, where researchers attempted to extend this model to increase its ability to explain people's choice in technology adoption. For example, Kwasi and A.F. Salam has extended the original TAM model by adding an extra variable called Shared Belief in the Benefit of the system to examine the implementation of ERP. This variable is again, fragmented into 2 sub variables which are Communication on Related Projects and Training on the System (Hanniya Abid and Umara Noreen, 2007). His studies found that shared belief in the benefit of ERP system affect both Perceived Ease of Use and Perceived Usefulness. Training and communications are also found positively related to shared belief. (Hanniya Abid & Umara Noreen, 2007). Similarly, Martinez Torres, Toral Martin, Barreco Garcia, and Gallardo Vazquez utilized TAM to study influencers of E-learning. They adjusted the model significantly and by adding various other dimensions such as Enjoyment, Variablity, Communicativeness, Feedback, etc. The studies interestingly found that Perceived ease of use has no impact on the adoption of E-learning, which opens up a new perspective on technology adoption in the aspect of education (Hanniya Abid and Umara Noreen).

Various versions of TAM model have been created and explored to find out the most important determinants in people's decision to adopt a technology. In recent literature, the strictness of this model has been more loosely defined, and many other variables have been used to replace Perceived Ease of Use and Perceived Usefulness. Lavin Aghaunor (2006) confirms the importance of technology aptitude in e-adoption decision. By technology aptitude, he means the banks competency inn electronic world, banks' incumbent ICT structure and resources set out for technology decisions. His study also found that commitment to E-commerce from top management is the key for banks' adoption of E-banking since the study was conducted in the context of Nigeria, a developing country; Lavin also stressed the importance of the government's E-readiness in shaping banks' decision of adopting E-banking (Lavin Aghaunor, 2006).

Reinforcing Lavin's findings on the strong relationship between Banks' e-competency and the level of technology adoption, Yahya Dauda, Mphil found that in Malaysia and Singapore, the decision on whether or not to adopt E-banking depends largely on experience with the Internet and banking needs. Moving a little beyond the sphere of capacity, he also found a strong correlation between banks' trust in the security of the technology they are adopting (Yahya Dauda, Mphil, 2007). Interestingly enough, the subject of banking security is prevalent in most researches on E-banking adoption among developing countries. In his exploratory research in

Pakistani's bank E-readiness, Hanniya Abid also concluded that trust is the number one factor that influences the decision to adopt E-banking among both banks and end-users.

A more comprehensive look at the reviews would show that network security and technology aptitude is just two sides of a coin. That means, according to these researches, up to this point, the most influential factor in firms' decision to e-adopt is probably still their capacity in technology. Understandably, firms in developing countries are more reluctant about this prospect since the ICT platform and the average level of technology aptitude may not live up to the nuances of the applications that E-banking requires.

III. Methodology

In the effort to explore and/or confirm research questions, scholars have developed two approaches: qualitative and quantitative. According to Oliver, 2004, quantitative approach originated from the natural science's objective research methodology where scientists examine the relationship between one independent variable and several dependent factors. Causal relationship is the core of quantitative method, which is obtained through analysis of numerical data. Qualitative research is essential for decision makers to understand to what exact extent certain factors impact on the independent variable. On the other hand, qualitative research leans on a more comprehensive and institutive approach. It involves the use of qualitative data such as in-depth interviews, secondary documents research (desk research) and participants' observations to account for the research questions. Qualitative research is the way to go when researchers want to understand the big picture with all the nuances and dynamics. On the upside, qualitative research helps us obtain a comprehensive look at the matter in question. On the downside, it would not be able to offer accurate numerical answers on the impact of each researched dimension the independent variable in question.

Choice of research approach depends largely on the research concern. If we already nail down the influential factors on the matter in discuss, quantitative approach is the appropriate method to give a confirmatory results. Yet, if we are unsure of all the dynamics of the discussed matter, qualitative research is a better choice to give us an overview of the story before diving deeply into what really matters. Standing from this point of view, we have chosen the quantitative approach to address the questions in discuss. This research would be more of a confirmatory nature, where we would seek to answer the questions in focus through examining data and the correlation between dependent variables and variables.

3.1 Research model and hypothesis

In this research, we would use the original TAM model to investigate the determinants of E-banking adoption in Nam Dinh. As can be seen from the diagram below, we would seek to measure Perceived usefulness (PU) and Perceived ease of use (PEOU) and examine the relationship between these two variables and Attitude toward E-banking. We then would explore the correlation between AT and Intention of Use (IT). The questionnaire included in Appendix 1 have described all these four dimensions on Linkert 5 point scale so that we can later on express these relationship easily in numerical terms.

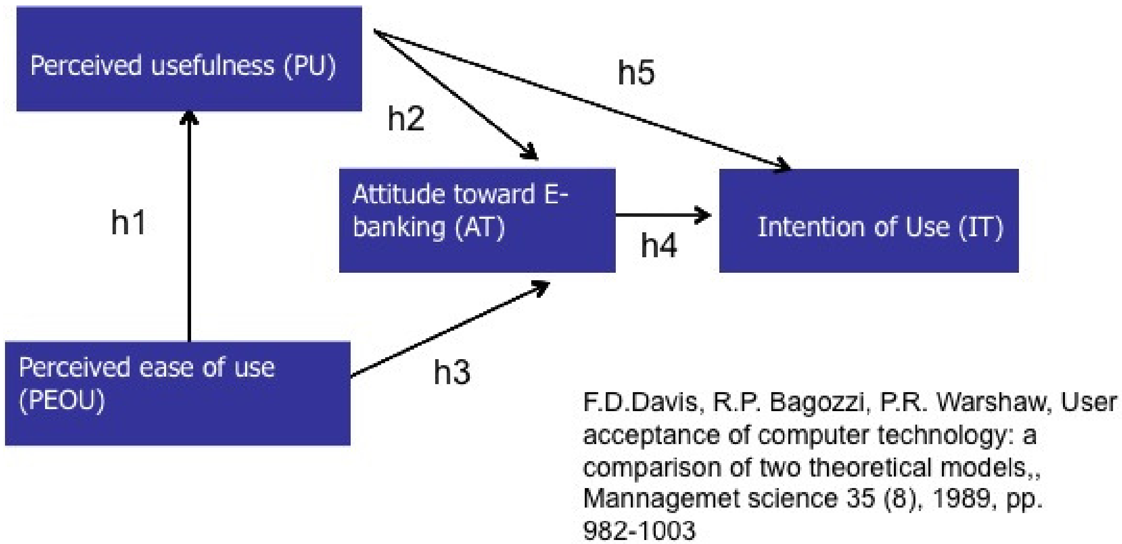

Figure 1: TAM model

H1: There exists a positive correlation between Perceived Ease of Use and Perceived Usefulness

H2: There exists a positive correlation between Perceived Usefulness and Attitude toward E-banking.

H3: There exists a positive correlation between Perceived Ease of use and Attitude toward E-banking.

H4: There exists a positive correlation between Attitude toward E-banking and Intention of Use.

H5: There exists a positive correlation between Perceived Usefulness and Intention of Use.

III.2 Data Collection Methods

This is a confirmatory research that evaluates the status quo of E-banking in Vietnam, the perceived influential factors on banks' adoption decision. To address these questions, we would collect numerical data by using the pre-designed questionnaires. We would seek to interview 10 banks in Nam Dinh, and in each of these banks we would interview 20 staff. The reason why we narrow down this population because, as explained above, a large portion of banks in Nam Dinh are designed to support poor people and within this group, the dynamics of services may not be market-oriented enough to include in this sample.

To approach these banks, we would send invitation letters to banks' administrators and their IT managers to attend our interviews. It should be noted that interviewing more high ranking management executives would be infeasible, therefore in the study we opt for these more practical choices. Interviewing IT managers would allow us to understand banks' current IT sophistication and their openness to new applications. In the mean time, administrators would give us a broad view of banks operations and the necessity and urgency of E-banking adoption. The interview would be recorded and put into transcripts for thorough analysis afterwards. The data churned out should include both demographic information and detailed points of view.

III.4 Sample Selection

As stated in the previous section, the selected sample would include 30 major banks in Vietnam. The sample structure is described in the table underneath.

Table 1: Sample Selection

Types of banks	Number	IT Manager (each bank)	Staff (each bank)
Joint Stock	5	1	19
State owned	5	1	19
Total respondents	200		

The core of most researches, again, includes comparisons and contrasts; we therefore choose to divide the sample into 2 different fragmentations. We fragment the sample by ownership; that is, state-owned banks vs. joint-stock and foreign banks. We assume that differences in ownership also influence strongly banks' policies and openness to technologies. It should also be noted that State-banks are normally more large scale than joint stock banks. As such, the difference in terms of scope of works may also account for their choices of technology adoption.

IV. Empirical Results

Following the survey plan discussed in chapter 3, we have approached 200 respondents from both joint-stock and State banks. We attempted to strictly follow the sector breakdown which involves targeting IT and staff at 5 joint stock banks and 5 state banks. The survey was conducted within a month; during which time we were able to reach 180 respondents. After thorough data screening, 4 questionnaires were deemed invalid. The final relevant data points were 178, which indicate that the response rate was 88 percent. This is a relatively high response rate, which may be due to the fact that the survey was conducted within the province of Nam Dinh. Another reason is our detailed list of respondents and close relationships with banks in the province.

IV.1 Sample Description

In this section I would focus on the demographics information of the surveyed sample. As mentioned in Chapter 3, the corresponding survey targeted mainly bank officials and IT managers at banks. The table below captures all basic features of the surveyed sample. The data are mainly presented in frequencies and percentages.

Table 2: Demographics of the surveyed sample

Measure	Item	Frequency	Percentage (%)
Bank type	Joint Stock Bank	74	41.1%
	State Bank	104	58.9%
Gender	Male	105	59.1%
	Female	73	40.9%
Title	IT	11	6.3%
	Bank Official	89	49.7%
	Management	47	26.4%
	Administrative	31	17.6%
Education	College	132	74.2%
	Master	19	10.7%
	Ph.D.	11	6.3%
	Other	16	8.8%
Age	22-30	74	42.1%
	30-40	54	30.2%
	40-50	29	16.4%
	Above 50	21	11.3%

As can be seen from the above table, there is an even split between the number of respondents from joint-stock banks and state banks (51.6% and 48.4% respectively). The majority of the surveyed respondents are aged between 22 and 40 (more than 70% in total). It is also apparent that this sample group is very well educated because more than 90 percent of them hold a college degree at least. This is understandable because the targeted group in the research desire consists of mainly key people in banks who are in the position to give a big picture of E-commerce applications in their workplaces. These percentages have therefore shown that the survey fieldwork has strictly followed the initial design and would therefore narrow the gap between research design and execution.

Table 3: Descriptive analysis for questionnaire items

Constructs	Items	Min	Max	Mean	Std.Deviation
PU1	178	1	5	3.0112	.94474
PU2	178	1	5	3.0169	.95358
PU3	178	1	5	3.0169	.95358
PU4	178	1	5	3.0056	.94777
PU5	178	1	5	3.0000	.98003
PU6	178	1	5	3.0112	.96251
PEOU1	178	1	5	2.9607	.89797
PEOU2	178	1	5	2.9944	.92362
PEOU3	178	1	5	3.0056	.94777
PEOU4	178	1	5	2.9944	.94777
PEOU5	178	1	5	2.9551	96738
PEOU6	178	1	5	2.9831	.96536
IT1	178	1	5	2.9326	1.08714
IT2	178	1	5	2.9382	1.14072
IT3	178	1	5	2.9775	1.13970
IT4	178	1	5	2.9326	1.12293
AT1	178	1	5	2.9494	1.52298
AT2	178	1	5	2.9438	1.51348

PU = Perceived Usefulness
PEOU = Perceived Ease of Use
AT = Attitude toward usage
IT = Intention to use (Refer to Questionnaire in Appendix 1)

The table above summarizes basic descriptions of 18 variables used in the TAM model. As can be seen, we use six variables to measure Perceived Usefulness (PU), six variables to measure Perceived Ease of Use (PEOU), four variables to measure the intention of use at surveyed banks, and two variables to measure attitude toward E-banking. All variables were measured using Linkert scale of five, with 1 equal "Totally disagree" and 5 equals "Totally Agree" (Refer to questionnaire in Appendix1).

As evident in the table, we can see that most respondents reflected slight reluctance when asked to voice their opinion on E-banking. The proof is that the Mean of most variables are around 3, which equals "Don't know" or "Unsure". It should also be noted when asked about intention of use and attitude toward usage, most respondents chose values lower than 3 (Mean values for these variables are smaller than 3), which equates Disagree. This indicates that the sample is slightly skewed toward unfavorable view of E-banking usage at their work place. Although these figures do not reveal the dominating trend, they somewhat show that an average respondents are somewhat reluctant about the idea of using E-banking.

IV.2 Validity and Reliability Testing

Before going on with hypotheses testing, it is crucial that we run solid data mining to make sure that the data is eligible for further investigation. There are various statistical measures as to whether a data set is reliable, one of which is Cronbach's Alpha Test. Cronbach's alpha is commonly used as a measure for internal consistency of data. Since several items are used to measure one construct, it is important that there is an acceptable level of internal consistency within each construct. Table….below demonstrates Cronbach Alpha statistics of each item. It is generally agreed that Cronbach's Alpha values should be at least 0.7 for an item to be reliable within a construct. As can be seen from table…, almost all Cronbach's Alpha values are from 0.8 tp 0.9, which indicates a high level of consistency within each construct. This consistency again indicates high reliability and it is therefore positive for us to move on with further analysis.

Table 4: Summary of Cronbach Alpha values of main factors

Factors	Items	Cronbach's Alpha
Perceived Usefulness	6	0.8625
Perceived Ease of Use	6	0.837
Intention of Use	4	0.859
Attitude toward usage	2	0.808

To verify the validity of each item, we attempt to use factor analysis approach. Factor analysis is a statistical method which aims to find joint variations between observed variables in order to identify data reduction possibilities. If factor loadings within each components are bigger than 0.5 then the component's level of validity is high. As can be seen from Table 5, all factor loadings across four components exceed 0.5, which indicate strong validity.

Table 5: Factor analysis

VARIMAX Rotated Component Matrixa

	Component			
	Perceived Usefulness	Perceived Ease of Use	Intention of Use	Attitude toward using
AT1				.814
AT2				.802
PU1	.864			
PU2	.871			
PU3	.868			
PU4	.867			
PU5	.844			
PU6	.861			
PEOU1		.823		
PEOU2		.830		
PEOU3		.832		
PEOU4		.860		
PEOU5		.827		
PEOU6		.848		
IT1			.837	
IT2			.847	

IT3	.872
IT4	.881

Table 6 illustrates the Eigen values and cumulative percent of variance. Consistent with the factor loadings analysis above, all four components have their Eigen values greater than 1, which indicates high significance in explaining technology acceptance process. A further investigation shows that:

For Perceived Usefulness, the cumulative percentage of variance explained by 6 items, are 98.5%.

For Perceived Ease of Use, the cumulative percentage of variance explained by 6 items, are 96.1%.

For Intention of Use, the cumulative percentage of variance explained by 4 items, are 95.3%.

For Attitude toward usage, cumulative percentage of variance explained by 2 items, are 96.0%.

Table 6: Eigen values and Variance

Factors	Eigenvalues	Cumulative %
PU	1.972	98.582
PEOU	5.768	96.141
IT	5.721	95.348
AT	3.842	96.040

These percentages show that the choices of factors in explaining technology acceptance were highly relevance as the components have covered a high level of variance.

IV.3 Regression Analysis

To test hypotheses proposed in 3.2., we would use linear regression analysis approach. Linear Regression approach use linear combinations to find relationships between independent and dependent variables. According to 3.2., we need to test 5 hypotheses as follows:

H1: There exists a positive correlation between Perceived Ease of Use and Perceived Usefulness.

H2: There exists a positive correlation between Perceived Usefulness and Attitude toward E-banking.

H3: There exists a positive correlation between Perceived Ease of use and Attitude toward E-banking.

H4: There exists a positive correlation between Attitude toward E-banking and Intention of Use.

H5: There exists a positive correlation between Perceived Usefulness and Intention of Use.

To examine the relationship between these variables, we would run three linear regression analyses. First, the relationship between Perceived Usefulness and Perceived Ease of Use will be examined (H1). Next, we would study the correlation between Perceived Ease of Use, Perceived Usefulness and Attitude toward usage (H2,H3). Finally, we would focus on the relationship between Attitude toward usage, Perceived Ease of Use and Intention of Use (H4, H5)

Table below summarizes the regression results for testing hypothesis 1: there exists a positive relationship between Perceived Ease of Use and Perceived Usefulness. The results shows that a positive relationship between these two variables exists at significance level 0.001 (F = 181.186, p=.000, t = 13.461). We therefore accept hypothesis 1 that there is a significant positive relationship between Perceived Usefulness and Perceived Ease of Use. R-square value of 0.507 indicates that Perceived Ease of Use can 50.7% of the times explain Perceived Ease of Use. The remaining 49.3% of the times could be explained by other latent variables.

This indicates that Perceived Ease of Use plays an important role in explaining the variance in Perceived Usefulness, other things equalled. We can therefore come up with the conclusion that whether a respondent finds an E-banking application easy to use will significantly influences that person's notion of whether that application is useful or not.

Table 7: Regression coefficients for H1

Factors	Constant	Standardized Coefficients β	t-value	R2	Adj-R2	F value	Sig.
Perceived Ease of Use	0.881	.712***	13.461	.507	.504	181.186	.000

Dependent variable: Perceived Usefulness
***p<0.001, **p<0.01, *p<0.05, +p < 0.1

The corresponding regression is as follows:

Perceived Usefulness = 0.881 + 0.712 * Perceived Ease of Use + e

Relationship between Perceived Usefulness and Attitude toward Usage

Relationship between Perceived Ease of Use and Attitude toward Usage

The results of linear regression analysis for factors influencing Attitude toward usage are summarized in Table…. According to these results, there is a significant positive correlation between Perceived Ease of Use and Attitude toward usage. Similarly, there exists a positive relationship between Perceived Usefulness and Attitude toward usage. These correlations are confirmed at significance level 0.001 with very positive goodness of fit, (t=7.056 and 4.284, F = 112.835, Sig = .000). Also, the fact that R-square equals .563 means that 56.3 percent of the time the combination of these two factors can explain the variance in Attitude toward usage of E-banking. This figure presents a good explanation capacity of these two factors for Attitude toward usage. We therefore accept hypothesis 2 and hypothesis 3. We can conclude that Perceived Ease of Use and Perceived Usefulness are important indicators that an average respondent in this sample will have positive attitude toward using E-banking applications. In other words, if a respondent finds an E-banking application easy to use and useful, he or she will be more likely to have positive attitude toward using it in the future.

Table 8: Regression Coefficients for H2,3

Factors	Constant	Standardized Coefficients β	t-value	R2	Adj-R2	F value	Sig.
Perceived Ease of Use		.502***	7.056	.563	.558	112.835	.000
Perceived Usefulness	-.973	.305***	4.284				

Dependent variable: Attitude toward usage
***p<0.001, **p<0.01, *p<0.05, +p < 0.1

The corresponding regression is as follows:

Attitude toward usage = -.973 + .502*Perceived Ease of use + .305* Perceived Usefulness + e

Relationship between Attitude toward Usage and Intention to Use

Relationship between Perceived Ease of Use and Intention to Use Linear Regression results for hypothesis 4 and hypothesis 5 also confirms that these hypotheses are correct. It can be seen from Table…that the relationship between Attitude toward usage and Intention to Use and that between Perceived Usefulness and Intention to Use are significant. The strength of goodness are shown in good indicators such as F-value equaling 99.743, and t values for two coefficients equaling 2.367 and 8.861. The R-square value of .533 indicates that 53.3% of the times the variance in the intention to use E-banking applications at banks can be explained by the combination of Attitude toward Usage and Perceived Usefulness.

Table 9: Regression Coefficients for H4,5

Factors	Standardized Coefficients β	t-value	R2	Adj-R2	F value	Sig.
Attitude toward usage	.163**	2.367	.533	.527	99.743	.000
Perceived Usefulness	.611***	8.861				.019

Dependent variable: Intention to use

***p<0.001, **p<0.01, *p<0.05, +p < 0.1

However, this time there is a difference between confidence levels of the two factors. With p-value equaling .000 and .019 respectively, it can be said that: We are 99.9% confident that there is a significant positive relationship between Perceived Usefulness and Intention to use, whereas, we are 99% confident that there is a significant positive relationship between Attitude toward Usage and Intention to Use. We therefore accept hypothesis 4 and 5 that there exists positive correlation between Attitude toward Usage and Intention to Use as well as between Perceived Usefulness and Intention to Use. Presumably, this indicates that whether a respondent chooses to use an E-banking application depends on if he or she finds it useful and has positive attitude toward it.

It should, however, be noted that perception of usefulness plays a more important part in a person choice of using an application as opposed to their attitude toward it. (Coefficients of PU and AT are .611 and .163 respectively, t values of PU and AT are 8.86 and 2.37 respectively). This result implies that the most important point for a surveyed respondent to choose to use an E-banking application is perception of usefulness. While Attitude toward usage also plays a role in this decision, it may not be overly important considering the results of this survey.

The corresponding regression is as follows:

Intention to Use = -.413 +163*Attitude toward Usage+611* Perceived Usefulness + e

Figure 3 below has summarized all the relationship between factors and their corresponding coefficients

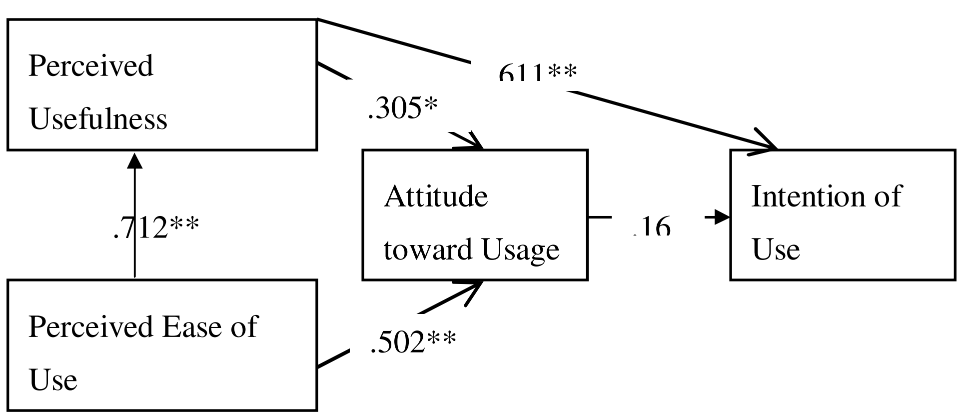

Figure 1: Regression model

To sum up, table 10 below has summarizes all hypotheses testing results in this research.
Table 10: Hypotheses testing summary

Research Hypotheses	Results
H1: There exists a positive correlation between Perceived Ease of Use and Perceived Usefulness	Supported
H2: There exists a positive correlation between Perceived Usefulness and Attitude toward E-banking	Supported
H3: There exists a positive correlation between Perceived Ease of use and Attitude toward E-banking	Supported
H4: There exists a positive correlation between Attitude toward E-banking and Intention of Use	Supported
H5: There exists a positive correlation between Perceived Usefulness and Intention of Use	Supported

V. Conclusion and Recommendation

In this research we seek to investigate factors influencing Nam Dinh's banks' decision on whether or not to adopt E-banking using the Technology Acceptance Model developed by Davis, Bagozzi and Warshaw. This model assumes three most important factors influencing user's decision of adoption of a technology, which are: Perceived Usefulness, Perceived Ease of Use and Attitude toward Usage. We assumes that there are positive relationship between these factors and Intention of Use, which indicates that Perceived ease of Use, Perceived Usefulness and Attitude toward Usage would positively influence a person's choice to adopt E-banking in Nam Dinh.

A survey on a sample of 200 people across 10 banks in Nam Dinh has resulted in a data set of 178 valid data points. Thorough data examination has shown confirmed our initial assumptions that Perceived Usefulness, Perceived Ease of Use and Attitude toward Usage have a positive relationship with Intention to Use. It should, however, be noted that Perceived Usefulness plays the most important role in determining banks' intention to use an E-banking applications. Perceived Usefulness is also the driving factor underlying a respondent's notion of whether an application is useful or not; similarly, this factor also strongly influences respondent's attitude toward E- banking usage.

V.1 Managerial Implications

Firstly, this thesis has studied acceptance of users for e-banking system. Thereby, a model of factors affecting the adoption of e-banking in the banking field has been developed, paving the way for future research and applications continue to expand this model to more the study factors affect to user's acceptance of e-banking system in the banking field. Moreover, the findings stress strongly on the role of Perceived Usefulness on bank's intention to adopt E-banking applications. This finding has very straight forward meaning to management and leaders of banks who seek to expand the use of E-banking within their banks. That is, in order to convince staff to use E-banking applications extensively, it is crucial to show them how these applications benefit their work and their performance in both long and short run. It is also important for banks' management to pay special attention to the level of usefulness of the E-banking applications that they choose to make sure that they will be used widely later down the road.

Another point to note is that, the idea of usefulness here should be seen from the perspective of users. "Perceived Usefulness" here means what most users find useful. Therefore, before choosing which E-banking applications they should apply across the banks, it is necessary for management to conduct an internal survey as to what functions staff at all levels find useful for their work. This is especially important to note because sometimes management's view and staff's perception of usefulness do not match. Such a survey may reconcile the difference and guarantee more sustainable development of E-banking. This finding should be incorporated into management's strategic point of view to build a comprehensive solution. Since Perceived Ease of Use also significantly influences respondent's attitude toward using E-banking applications, another implication that managers should take into consideration is the user-friendliness of the applications they choose to implement. For the use of such applications to be long term and sustainable, it is highly important that banks management seek to make it easiest possible for their staff to use these software. In-depth training is also much needed to improve the notion of "Ease of Use" for banks' staff. In so doing they can significantly improve staff's attitude toward these new technology.

V.2 Policy Maker Implication

This finding also bears significant meaning for policy makers who seek to roll out E-banking on a larger scale. Because such introduction is similar to marketing a product to a targeted population, it is essential that policy makers take into account Perceived Usefulness and Perceived Ease of Use in their execution. For example, Usefulness and User-friendliness could be counted as one of the criteria for an E-banking application or program to be approved or implemented because only by following these criteria can we guarantee sustainable usage. Not only should they be used as Pre-introduction criteria, Perceived Usefulness and Perceived Ease of Use should also be counted as Post-introduction meters to judge whether an E-banking program was successful or not. Such information would be of great significance for future implementation of other programs.

Software Developer Implication

More than anyone else, software developers should take the findings of this research most seriously because it bears great implication about how their products should be improved in the future. A sound conclusion for software developer is that Usefulness sand User friendliness are two most important factors to consider as they decide to launch a new product in E-banking. The definition of Usefulness and User-friendliness should be customized based on specific circumstances. Under these situations, further researches need to be conducted to obtain more tangible production orientation.

V.3 Limitations

A limitation we ran into as we conduct this study is the differences of experiences in E-banking across our respondent population. Even though we have sought to reach respondents with similar background, education and positions at different banks, it is still impossible to guarantee that these respondents have the same perception on Usefulness, User-friendliness, or the level to which an application has supported their performance at work. Also, since banks do not implement similar E-banking applications, it is even harder to make sure that these respondents' definitions of usefulness and user friendliness are the same. This variety may be the main reason for the missing variance that the R-square values in most regressions.

Secondly, because the study was conducted within the province of Nam Dinh, among a small group of banks, the results might not be representative of the whole population. Even though we have sought to segment the surveyed population into State banks and Joint stock banks to increase variety, the fact that these banks are too close in proximity may make the results somewhat skewed.

Finally, since Nam Dinh is not the country's technology hub, applications of E-commerce still remain limited. Respondents' limited experience with E-banking would also be one of the factors that may hinder the accuracy of their answers.

V.4 Further Study

To overcome the aforementioned shortcomings, we propose several solutions to improve accuracy. Firstly, we need to screen out banks with similar experiences in terms of both E-banking usage and duration of use among respondents to make sure that we can hold other things equal as we conduct the relationship between these factors. Secondly, to improve neutrality and objectivity, we need to increase the sample size as well as the regions we cover so that the results will be representative of the populations of banks across the country. Thirdly, to gain more insights from such study, it is also highly recommendable that we conduct comparisons across different groups of respondents. For example, management point of view in E-banking usage may be a few steps further from Staff's perception. Such results would bear great importance for managerial strategies in implementing such applications extensively and intensively.

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