STOCK’S PRICE BEHAVIOUR AROUND CORPORATE MERGER AND AQUISITION ANNONCEMENTS: EVIDENCE FROM THE NYSE

by

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Abstract

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Efficient price discovery is one of the most important qualities of a financial market. Assessing a market's efficiency of price discovery is a challenging topic because efficient prices are not directly observable. It is not clear how to measure the extent to which actual prices conform to efficient prices. In this study, we use a methodology based on a state space model which deals naturally with short-term microstructure noise and enables the estimation of the unobservable prices and by implication, the pricing error. We investigate the contribution of non-instantaneous price discovery to intraday stock's price volatility around US corporate merger and acquisition announcements for a sample of 53 NYSE stocks from 2004 to 2008 using the TAQ data.

Specifically, we model and estimate non-instantaneous price discovery effects that are associated with partial price adjustments to merger and acquisition (M&A) announcements for target names. We estimate price impacts from order imbalances that create pressure on a stock's price and cause a stock's price to move in a direction of order flow using one minute differencing intervals in the day of the merger news and the following day excluding the first 30 and the last 30 minutes of the trading session. Partial price adjustments may result in market over/under reaction to M&A news. To address this issue we also model and estimate market over/under reaction to

merger news. We analyze the estimates of price impact and market over /under reaction to M&A announcements by contrasting the results in an M&A environment with the estimates observed in no-news days and before M&A news days. Our results shed light on price discovery around M&A announcements and its contribution to accentuated stock's price volatility.

We find evidence of a protracted price discovery process following M&A news that takes at least two days after public merger announcements. Our findings reveal a significantly more informative period in two days following M&A announcements with the information flow per unit of time a factor 2 higher compared to the pre-announcement period and no-news days.

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Chapter 1: Introduction

Trading around corporate merger and acquisition (M&A) announcements has revived the interest of researchers due to the recent corporate merger boom (Morgenson, 2006). Most of the prior work on trading around merger news is focused on analyzing trading behavior of market participants. Moreover, evidence of the effect of M&A announcements on price discovery around acquisition events is contradictory as empirical studies on trading behavior of investors have shown mixed results. Mitchell and Pulvino (2001) and Officer (2007) are examples of risk arbitrage literature that examines post-announcement trading activity of risk arbitrageurs and indicates that there is a significant activity of arbitragers who buy stocks of takeover target after public M&A announcement to take advantage of uncertainty if the takeover deal materializes in the future.

Rosa, To and Walter (2007) is an example of literature on high-frequency institutional trading behavior around M&A news. The authors examine post-announcements price drift phenomenon using daily trading behavior of UK fund managers around M&A announcements and show that they trade on perceived good news. Some prior studies on mergers indicate that the stockholders of target firms earn significant abnormal returns not only in the period around the announcement but also in the weeks after the announcement. For example, Jensen and Ruback (1983) find an average abnormal return of 20% to target stockholders of successful mergers.

Other studies on M&A document increased trading volume and significant price run-ups for target companies in a pre-announcement period. Chakravarty (2001) finds that institutional medium-sized trades contribute to significant price impact before takeover announcements. Griffin, Shu and Topaloglu (2007) analyze institutional and individual trader’s behavior before merger announcements for

NASDAQ-listed target stocks and find that institutional investors are net sellers and therefore their trading cannot predict takeover premium. In contrast, the authors find that individual investors build up net buying positions in the pre-announcement period.

Daouk and Li (DL, 2009) find that target stocks that are traded by institutional investors do not show significant price run-ups prior to takeover announcements. DL (2009) provides an explanation that institutional investors do not trade aggressively to induce price impact. The authors also find that on the announcement day most institutional investors tend to reverse their trading positions to cash in except for brokerage firms that act as merger arbitrager and continue to buy target shares. Specifically, DL (2009) show that daily net buying pressure from order imbalances decays starting from the announcement day and has an inverted U-shape.

Gao and Oler (GO, 2008) document increased trading volume and find active-selling in target stocks that off-sets increased active buying in a period preceding acquisition announcements. They use this finding to explain why, despite of a surge in trading volume, the M&A information delays to impound into price in the pre-announcement period. The authors also explain this finding by rational behavior of sellers who trade on market over-reaction to M&A rumors in the pre-announcement period that in most cases fail to materialize into public announcements. These findings indicate that market tends to be less one-sided in a period preceding an acquisition announcement.

There are prior studies that concentrate on effects on M&A announcements on trading costs of target stocks that are measured by the spread. These studies also show mixed results. For example, Foster and Wiswanathan (1994) find that spread increase before merger news, whereas Draper and Paudyal (1999) provide evidence that spreads decrease prior to M&A announcements. Jennings (1994) does not reveal any significant variation in spreads in the pre-announcement period.

In contrast to prior literature, our study is focused on understanding intraday price discovery around M&A news events. While most prior work discusses trading around takeover announcements using low frequency (daily, weekly, monthly) data, our study attempts to obtain more insights into minute by minute dynamic price adjustments. More specifically, we assess dynamic price adjustments of target stocks such as price impact and market over/under reaction to M&A announcements that are due to non-instantaneous price discovery and their contribution to the pricing error. Dynamic price adjustments to M&A news are jointly examined with market order imbalances. In contrast to most prior work that estimates statistics of stock returns and order imbalances without an explicit model that links the underlying dynamics of both variables, we set a dynamic model that links price changes to changes in order flow.

The dissertation attempts to shed more light on intraday price discovery around M&A announcements and to answer the following related questions:

1. what period (pre-announcement or post announcement) does indicate more informed trading and reveal significant price adjustment to M&A news?
2. if price adjustments lead to market over or under reaction to takeover news?
3. what period is associated with inflated pricing errors and, by implication, with inflated implicit transaction costs?
4. how the implicit trading costs due to pricing errors do compare with trading costs measured by the spread?

Paroush, Schwartz and Wolf (PSW, 2010) argue that price discovery is a major factor that contributes to volatility surges that follow public news release and therefore, to implicit trading costs. If the spread is much smaller than the pricing errors due to imperfect price discovery, then the former is a misleading metrics of trading costs around M&A announcements. We contribute to the existing literature by examining the pricing errors around M&A announcements as a measure of implicit trading costs and comparing them to trading costs that are measured by the spread. The main accomplishment of this study is that it proposes a model that allows for empirical estimation of the unobservable efficient price and, by implication, the pricing error.

M&A announcements are interesting news events to study price discovery. They are far less anticipated than other corporate news such as earnings announcements and have significant impacts on target shares prices. They are also very interesting because trading around merger news represents a situation when the market digests highly significant and uncertain information.

Price discovery is a dynamic process of searching for values that reflect a broad market's interest in holding shares given the news. The ability of the market to impound new information into stock prices with minimal intra-day price volatility requires accurate price discovery. Price volatility contains two components: a good one that is accounted for by price adjustments due to news about fundamental values, and a bad one that is process-driven and associated with transaction costs. Consequently, we can classify volatility as fundamental volatility and technical volatility (Schwartz and Francioni (2004)). Lower trading costs imply a lower technical component of volatility, more accurate price discovery, and better market quality.

Efficient price discovery is the main function of an equity market. However, this issue has not been an adequately recognized regulatory goal in the past (Schreiber and Schwartz (1985)). The topic received attention in early 2004 when the Securities and

Exchange Commission released the market data proposal of the Reg NMS which suggests rewarding markets for providing price discovery through liquidity that would flow to the best automated quote. Harris, McInsh and Wood (2008) examine the impact of Reg NMS on price discovery of DJIA stocks and find that NYSE and NASDAQ prices become more informative (e.g. prices reflect increased impounding of information) after the implementation of Reg NMS.

Since trading is a zero-sum game, market participants' attitudes toward elevated process-driven volatility may be different depending on whether it is a source of their revenue or a cost. However, it is clear that accentuated technical volatility is costly to the market in aggregate. There is a great chance of significant price movement in a market with accentuated volatility in a short period of time which makes trading more difficult. This price uncertainty discourages trades and makes portfolio returns less certain.

In a perfectly liquid, frictionless environment, price adjusts instantaneously to new information arrival into the market. In reality price discovery is a complex dynamic process since price does not adjust instantaneously to new level based on news due to friction factors. To avoid adverse market impact, market participants tend to slice and dice their orders causing a delay in a price discovery process. Also, it takes time for divergent expectations of investors to converge through an adaptive valuation mechanism. Hence, prices cannot be instantaneously in equilibrium, and cannot instantaneously reflect all available information. It is worth noting that large institutional investors also send their orders to dark pools to execute against hidden liquidity which on the one hand, may adversely affect price discovery due to fragmented order flow. On the other hand, sending large orders to dark pools instead of an exchange may facilitate price discovery in the sense that it decreases a chance of momentum trading that is caused by slicing and dicing of large orders (Schwartz, 2009).

In response to new information about the underlying security, market participants collectively discover the new consensus value of the stock by placing their orders that reflect their opinion about the fair value. This results in price impact from information triggered order flow. Price impact is partial price adjustment to news. In the process of finding its consensus value, a stock's price may swing up too high or go down too low resulting in prices bouncing between two levels: a higher one and a lower one. Moreover, price swings may be associated with market over or under reaction to news depending on the strength and duration of price impact from order imbalances. Therefore, market over or under reaction is a non instantaneous price discovery effect that fully depends on price impact. The concept of market over/under reaction to news has been introduced by Amihud and Mendelson (AM, 1987). They suggest that market over/under reaction to fundamental information is an important component of transitory price changes.

Price impact and market over/under reaction are partial price adjustments that are due to imperfect price discovery which exists because markets are not perfectly liquid, frictionless environments. These short-term oscillations are price discovery noise that translates into heightened intraday volatility and represents implicit trading costs. Partial price adjustments that are the result of protracted buying or selling pressure from order flow develop into price trends which we refer to as price momentum. Note that protracted buying or selling pressure may naturally be reinforced by momentum trading. This happens when agents chase a price trend thinking that a stock's price is still adjusting to its new level based on new information.

Previous studies on a price discovery process present two strands. One is a theoretical framework describing the trading environment and possible mechanism of a price formation in this environment. Another is empirical studies of price discovery effects without modeling a price discovery process per se. PSW (2010) is a theoretical framework that sets a stage to explain price discovery's contribution to accentuated price volatility following market openings or news events. This is a study that addresses a very complex question of how the information from diverse buyers and sellers, which may be too textured for any of them to fully articulate, is somehow incorporated into the price.

Specifically, PSW (2010) model an equity market where agents with divergent expectations exhibit the adaptive valuation behavior. Share prices are established through interactions of orders from agents who reveal their opinions about the underlying stock's price. Price discovery becomes a complex process that generates microstructure noise that contributes to accentuated price volatility following news events.

The asymmetric information approach is an alternative to the divergent expectations with adaptive valuations approach that attempts to explain price discovery. This second approach assumes homogeneity of expectations of informed trades which imply an assumption that information maps uniquely into security prices. For example, Kyle (1985) and Glosten and Milgrom (1985) explain accentuated intraday volatility by tactical trading of informed participants. These models predict a price process by examining the learning problem by market makers. Specifically, in these models the bid-ask spread is positively related to the proportion of informed trades.

Hasbrouck (1993) and Menkveld, Kupman and Lucas (MKL, 2007) present empirical studies of price discovery without modeling a price discovery process. Both studies allow for a decomposition of prices into an efficient (random walk) component associated with news innovations and a stationary (mean reversion) component due to market microstructure noise. Hasbrouck finds that a stock's price volatility is the highest at the beginning and at the end of the day. This accentuated volatility is due to heightened pricing errors. MKL (2007) study round-the-clock price discovery for Dutch cross-listed stocks on markets that do not fully overlap around specific intraday time points related to news release using a state-space model of a stock's price. They find that the overlapping period when both Amsterdam and NYSE exchanges are open is the most informative since it is associated with largest innovations in the efficient price in 24-hour price discovery period.

Another series of empirical studies examines behavior of important market microstructure variables such as volume, spreads and volatility around news events. Maloney and Mulherin (1992) study volume and volatility around stock splits. Voetmann (2008) examines changes in the bid-ask components around earnings announcements. Krinsky and Lee (1996) examine earnings announcement effects with the existence of asymmetric information about expected earnings.

This dissertation attempts to link two strands of literature together. We first propose a state space model that allows for empirical estimation of the efficient price and the imperfect price discovery effects associated with partial price adjustments to M&A news and, by implication, the pricing errors. We also examine these results in conjunction with the main market characteristics such as volume, trading activity, volatility, spread and asymmetry of order flow around M&A announcements to get more insight into a price discovery process.

Prior studies on price impact around M&A announcements indicate a protracted price discovery period that may take at least a week before and a week after merger announcements. We choose to concentrate on examining immediate price discovery effects during two days before and two days after takeover news. Like Sarkar and Schwartz (2009), we consider three time periods: two days before merger announcements, two days after, e.g. the actual day of M&A news and the following day and two days for which we try to exclude the possible news effects. Specifically, we choose two days from the period preceding M&A news excluding the 2 days before and 2 days after quarterly earning reports and major macroeconomic news, e.g. Core Consumer Price Index (CPI), Producer Price Index (PPI) and announcements on Employees Nonfarm Payroll.

Fleming and Remolona (1999) show that Core CPI, Producer Price Index and announcements of Employees on Non-Farm Payroll represent about a quarter of all 8:30 A.M. announcements that have very pronounced market impact. Similar to SS (2009) we remove days with the top 30% percentile of absolute value of excess close-to-close returns vs. the market index to further mitigate any news impact. We contrast our empirical results using three samples: the “Before”, “After” and “No-news”. We analyze price discovery using the TAQ data on a pooled sample of 53 NYSE stocks that were announced as a target in large merge and acquisition deals in the US from 2004 to 2008.

The short-term nature of trading friction factors influences the choice of the time differencing interval. The impact of short-term microstructure noise is washed out over relatively long time differencing intervals (for instance weekly or monthly). On the other hand, too short intervals would not allow us to capture trading friction because these factors would not significantly manifest themselves. For example, it would be difficult to estimate market impact over very short time periods since this is a result of protracted pressure in one direction from order flow. Our choice is a one-minute differencing interval, for it seems to be a good compromise. On the one hand, though shorter intervals are technically possible, assigning trades as being buyer or seller initiated is prone to error. This error can partially be mitigated by aggregating over time since shorter time intervals tend to comprise a smaller number of trades and thus a potentially larger standard deviation of order imbalances. On the other hand, though longer intervals are feasible, market inefficiencies would probably be less conspicuous. Kempf and Korn (1999) is an example of a study that uses one minute order imbalances and prices of German index futures to study the permanent impact of trades.

The dissertation proposes a state space model that allows for a decomposition of the actual price into the efficient price (random walk) and a stationary (mean reversion) component associated with market microstructure noise. A state-space modeling has increasingly been used in macro economics and finance. For example, Zivot, Wang and Koopman (2003) provide a survey of state-space models that are used in finance. Basdevant (2003) is a source of applications of state-space models in macro economics. Nevertheless, there are very few studies on price discovery in equity markets that use a state-space approach. There is the main type of price discovery problem that can efficiently be addressed using a state-space modeling: a decomposition of an observable price change into a transitory and a permanent component. State-space models use the Kalman filter to smooth data so that temporary short-term fluctuations that are due to microstructure noise can be separated from the long-term trend that is attributed to news about fundamental values.

MKL (2007) is a recent study that exploits a state-space model of a stock's price to examine price-discovery of cross-listed stocks.

The key innovation of this model in contrast to the model proposed by MKL (2007) is a joint estimation of the price-order imbalance dynamics. We are not aware of any other study on price discovery that exploits a state space methodology using price and order imbalances. The microstructure literature emphasizes the important role of order imbalances in stock's price dynamics. The appeal of order imbalances as a main determinant of price dynamics is natural. Market participants discover the price given news through interaction of their orders. Order imbalances reveal the overall market's mood to buy or sell a stock causing a stock's price to increase or decrease. Also, traders prefer slice and dice their orders to minimize the price impact of trades, thus causing positive autocorrelation in order flow. In turn, this positive correlation causes price pressure which gives rise to a predictive relation between order imbalances and future price movements. Of course, there is a bi-directional causality between price and order imbalances since agents put their orders based on observed prices. Brown, Walsh and Yuen (1998) find a daily bi-directional causality between order imbalances and price returns for stocks traded on Australian Exchange. Hasbrouck (1991) uses a bivariate vector autoregression model of intraday prices and order imbalances to investigate the information content of stock trades.

Most existing studies analyze the relation between order imbalances, as a determinant of price changes, and market returns in the context of the traditional Lee-Ready algorithm (Lee and Ready 1991) associated with market orders. Chordia and Subrahmanyam (2008) examine short-term horizon predictability of 5 minute returns from lagged 5 minute Lee-Ready imbalances using a comprehensive sample of NYSE stocks. They find a strong short-term predictability of price returns based on order imbalances. Plerou et al. (2002) is another example of a paper that focuses on market impact of the Lee-Ready imbalances using 5 minute aggregate transaction data from NYSE. We choose mid-quote price and the Lee-Ready aggregate order imbalance over one minute interval normalized by the total number of trades to form a vector of observations in our model.

The state-space framework views observed variables as representing noisy information about real, though unobservable, state variables that form a state vector. A-priori information about dynamics of unobservable state variables and their interaction is used to formulate a model equation. A model equation contains innovation terms that drive dynamics of the state variables. The concept of the efficient price as an equilibrium price in frictionless environment, which follows a random walk, has been introduced by Hasbrouck (1991). We use this concept to model unobservable price dynamics for our state-space model. The efficient price is driven by innovations with deterministic time-invariant volatility. These innovations are associated with news and have permanent price impact.

Empirical studies, for example Bouchaud et al. (2004), reveal that order flow is a long memory process with a slowly decaying autocorrelation function of power law. As we discussed above, it is a result of order splitting that causes order flow to be a highly persistent process both in sign and volume. This reflects the fact that the revealed liquidity is very small even on liquid markets. We suggest a first order autoregressive process to describe an underlying dynamic of the normalized Lee-Ready imbalances. Recent studies reveal that first order lagged order imbalances provide a significant explanatory power into a high frequency dynamic of order flow.

Observations contain noisy information about unobservable state variables. They are linked to state variables through an observation equation that contains unobservable disturbances. These disturbances are deviations of actual signals from states and are referred to as noise. The noise term is associated with temporary fluctuations caused by short-term factors. For example, the actual transaction price deviates from the efficient price due to such market microstructure factors as bid-ask spread, market impact, momentum trading and price discovery noise. As we discussed above, this study focuses on the latter factor by examining partial price adjustments that are due to imperfect price discovery, e.g. price impact and market over/under reaction to M&A news.

Like MKL (2007), we suggest using the mid-quote as a proxy for the unobservable efficient price since they are not affected by the bid-ask bounce. The constructed Lee and Ready order imbalances from transaction and quotation data represent noisy information about true but unobservable order imbalance. The difference between the observable and the unobservable order flow is due to trade classification algorithm errors. Theissen (2000) tests the accuracy of the Lee-Ready algorithm using transaction data from the Frankfurt Stock Exchange and finds that the method classifies a relatively small 73% of transaction correctly. The author maintains that misclassification of trades may lead to a systematic bias of the empirical results. O'Hara (1999) examines the accuracy of the algorithm using NASDAQ transaction data and documents that the algorithm correctly classifies 81% of the transactions. The pricing error in our model (that is the difference between the observed mid-quote and efficient price) is associated with partial price adjustments: price impact, market over/under reaction to news and a residual term.

Price impact in our model is captured by the impact from contemporaneous order imbalances associated with slicing and dicing, liquidity events and technical momentum trading. Slicing and dicing comes from sophisticated investors who may obtain more insights into share value by processing publicly available information. In the presence of such insights they tend to slice and dice their orders to hide market impact. Investors trading for other reasons than information are usually referred to as liquidity traders. Their order flow is associated with liquidity events. Technical momentum traders do not posses information and make their investment decision based on observed prices. They chase price trend thinking that price is still moving to its new level and push price away from the underlying value. A question about who is responsible for price impact around M&A announcements: institutional traders, individual market participants or corporate insiders is outside of the scope of this dissertation.

Market over/under reaction to news is modeled as a price reaction to the innovations in the efficient price. This modeling of market over-under reaction has been adopted from MKL (2007) and AM (1987). Market reaction is determined by price adjustments due to pressure from order flow. We cannot assume ex-ante if a price impact results in market over/ under reaction to news. As we noted above, the result depends on the strength and duration of price impact. Of course, there are major factors such as precision, magnitude and dissemination of information that effect how investors react to news and, subsequently, how this reaction translates into orders placed by agents (Pritamani and Singal (2001)).

The residual term represents a part of pricing error that has not been fully captured by the price impact from contemporaneous order imbalances or market over/ under reaction to news. For example, our model uses explicitly only the contemporaneous order imbalances to capture the main component of the price impact from order flow so the residual impact from high order lagged imbalances is reflected in the residual term. The recent literature documents a nonlinear concave price impact function of the Lee-Ready imbalances. Plerou et al. [2002] examine 5 minute Lee-Ready order imbalances and price returns of NYSE stocks and find that price impact is inflated at smaller order imbalances and flatters out at larger imbalance values. Note that our model uses a linear approximation for the price-order imbalance relation, so the residual term contains nonlinear component of the price impact. The residual term also reflects rounding errors due to the discrete price grid.

Note that the Kalman filter provides a smooth estimate of the efficient price which is a theoretical step wise function that changes values immediately based on arriving information. Therefore, our smooth estimate of the efficient price serves a directional proxy for the unobservable random walk. However, we are primarily interested in a relative magnitude of the pricing errors around M&A announcements vs. no-news days rather than in their absolute values. Our state space model assumes normality, homoscedasticity and serial independence of the innovations and error terms. To address the homoscedasticity assumption, we analyze trading from 10 A.M. to 3:30 P.M. to mitigate the intraday volatility smile that has been documented as a U-shape pattern in a sizable microstructure literature.

After establishing the model, the study assesses and discusses minute by minute price adjustments around M&A news and their contribution to implicit trading costs. The reminder of the dissertation is organized as follows. Chapter 2 is a literature review. Chapter 3 provides a discussion of divergent expectation environment with adaptive valuations vs. asymmetric information. Chapter 4 provides a detailed model description. Chapter 5 describes the data. Chapter 6 reports empirical findings. Chapter 7 is diagnostic testing: specification and robustness checks. Chapter 8 concludes the study.

Chapter 2: Literature Review

The literature on price behavior around M&A announcements covers many aspects of takeover activity. A series of prior studies examine the market microstructure effects of M&A announcements on target firms. This literature provides evidence on price run-ups, increases in trading volume and changes in the spread around merger announcement and focuses on explaining price impact by trading behavior of different groups of investors.

There is a series of prior studies that examine price and volume changes in the pre-announcements period. One of the debatable questions of such studies is whether price run-ups are due to market anticipation of news or trading on insider information. Keown and Pinkerton (1981) detect abnormally high daily returns 7 days prior to the announcement day. They also provide evidence of higher trading volume in target stocks three weeks before the announcement. The authors argue that their findings of abnormal returns prior to the announcement day are related to inside information leakage.

Subsequent studies by Jarrel and Paulsen (1989) and Draper and Paudyal (1999) confirm the phenomenon of price run-ups and increased volume over approximately the same period before the announcement date. In contrast, these studies explain price run-ups before the announcement by trading on rumors. Chakravarty (2001) also documents a price impact prior to takeover news. The author examines price impact using a sample of NYSE stocks and finds that medium-sized trades from institutional investors are most informative. Griffin et al. (2007) study NASDAQ-listed target stocks and find that price impact in the pre-announcement period is associated with net buying positions of individual investors whereas institutional investors provide liquidity before merger announcements. The authors argue that pre-announcement bid market activity is mostly due to market anticipation of news.

Hasbrouck (1991) finds that there is a permanent price impact of information-driven trading before M&A announcements for NYSE-listed stocks. The author suggests decomposing of the variance of changes in the efficient price into trade correlated and – uncorrelated components. The trade component that is associated with trades is used as a measure of informativeness.

There are also prior studies on price impact in the post-announcement periods. Risk arbitrage literature (Mitchell et al. (2004) and Officer (2007)) examines behavior of risk arbitragers in the post-announcement period and find that price run-ups are due to net buying positions of investors who take advantage of uncertainty whether the announced merger deal will consummate or not. In other words, investors capture the arbitrage spread in stock mergers. In case of cash mergers, the strategy of such investors is buying target shares and holding them until a merger deal closes. In case of stock mergers the situation is more complicated. Investors buy target shares and also trade shares in acquiring firm to isolate transaction risk.

The recent study by Daouk and Li (2009) focuses on daily trading behavior of institutional investors before and after M&A announcement. The study uses institutional trading dataset on target US stocks from 1993 to 2004 that is coupled with NYSE Trades and Quotes. The authors find that institutional investors start accumulate target shares as earlier as 30 days before the announcement day. The statistically significant net buying orders are reveled around -16 day. Daily net imbalances in excess of average daily net imbalances over the entire period reveal an inverted U-shape over a month before and after the announcement day. Most institutional investors revert their positions in the target stocks after M&A news except for brokerage firm that continue to buy shares in target stocks to speculate on final deal.

Though the authors detect statistically significant order imbalances in the pre-announcement period, they do not find significant price run-ups since the magnitude of the order imbalances are relatively small. They argue that the absence of the significant price impact of institutional trades before the announcement day is due to hiding market impact through algorithmic trading or breaking orders into smaller trades.

Gao and Oler (2008) confirm the absence of significant price run-ups in the period before merger news. Specifically, the study examines daily trading volume and order imbalances of NYSE and Amex – listed targets traded by institutional investors from 1993 to 2004. The authors find a significant surge in daily trading volume around -14 day. However, they show that daily buy orders tend to off set daily sell orders at least up to -9 day. The authors argue that sellers are rational investors that respond to market overreaction to rumors about the anticipated merger deal and short sell the targets. This shorting causes a delay in impounding of the takeover information into prices.

Investor reaction to the information conveyed in the announcement is another interesting aspect of merger activity. In an efficient market price should adjust immediately to new information, so we should not be able to observe predictable price pattern such as price momentum or reversal indicating market under or over reaction to news. Lasfer et al. (2003) examine international market portfolios and provide evidence of short-term under reaction after extreme events. Pritamani and Singal (2001) discusses three dimensions of information events that impact market reaction: magnitude, precision and dissemination. Prior literature (Ryan and Taffler (2004)) suggests measuring magnitude by price changes. Trading volume proxies for precision of information, whereas the number of agents that receive the signal is a proxy for dissemination.

Spyrou (2007) studies short-term investor reaction to M&A announcement in the London Stock Exchange during the 1997-2006 period. The author examines daily investor reaction following merger news and controls for such factors as precision by separating M&A news that disclose financial information such as bid price and those that do not disclose the details of the deal, magnitude and dissemination. The findings indicate that market reacts efficiently to M&A announcements about target firms regardless of precision of information. Rosen (2006) provides evidence on the impact of a merger momentum on market reaction to M&A announcements. In other words, market reaction to takeover announcements is positively correlated to reaction of the market to the recent M&A news.

Another important aspect of merger activity that is widely discussed in the literature is trading costs around M&A announcements. Prior work on trading costs of target firms has shown mixed results. Jennings (1994) does not find any significant fluctuations in spreads before M&A announcements on an intraday analysis. Foster and Wiswanathan (1994) find increases in the spread in the preannouncement period. In contrast, Ascioglu et al. (2002) do not find that the spread increases before M&A announcements. Draper and Paudyal (1999) provide evidence that the spread decreases before the takeover announcements.

Most of prior work on trading costs measured by bid-ask spreads is concentrated on factors that determine the spread. Lipson and Mortal (2005) conclude that firm characteristics such as trading volume, volatility, number of analyst, number of market makers and number of shareholders are related to spreads. Roulestine et al.

(2003) provide evidence that dispersion of analyst forecasts about firm's earnings affect the spread. Kanagaretnam et al. (2005) study changes in spreads around earnings announcements and suggest that spreads are affected by quality of information about earnings. Mai et al. (2008) examine how mode of acquisition, method of payment and deal attitude impact the bid-ask spread of target firms around M&A announcements.

While trading costs measured by the bid-ask spread captures a dimension of market liquidity and market quality, it represents only an observable part of total trading costs to investors. PSW (2010) argue that price discovery is a major factor that contributes to the unobservable pricing errors and therefore, inflates implicit trading costs. In order to assess transaction costs incurred by investors around M&A announcements it is important to consider both the explicit and implicit components of trading costs.

In contrast to prior studies that typically examine daily price changes of target firms and market reaction to M&A announcements, this dissertation contributes to the literature by analyzing intraday, i.e. minute by minute price adjustments in response to order imbalances around merger news. This sheds light on how information about M&A deals gradually impounds into prices through interaction of orders of market participants. Moreover, in contrast to the prior literature, we consider both implicit and explicit components of trading costs around M&A announcements. The former relates to directly unobservable trading costs that are due to the pricing error occurring as a result of imperfect non instantaneous price discovery. The latter is directly observable trading costs that are measured by the spread. Our analysis contributes to better understanding of market efficiency of price discovery and total trading costs around merger announcements by assessing and comparing implicit trading costs measured by the dispersion of the pricing errors with the spread.

As noted, the fundamental challenge of assessing a market's efficiency of price discovery is that efficient prices are not directly observable and it is not clear how to measure the extent to which actual prices conform to efficient prices. To address the problem of unobservable efficient prices, microstructure literature suggests different methods for evaluating price movements in response to changes of information on fundamental economic factors. Our analysis of a market's efficiency of price discovery relates to several other approaches that study (1) the speed at which market prices adjusts to new information and (2) magnitude of pricing errors that represent difference between actual price and unobservable efficient price.

Amihud and Mendelson (1987) introduce a model of price adjustment. Their model distinguishes between intrinsic value of a security and its observed price. They attribute difference between the value and price to noise that is due to temporary liquidity needs, errors in interpretation of information and trading mechanism. However, their model assumes that price adjustments to new information and trading friction share the same dynamics. Price adjustments due to non-informational factors demonstrate how resilient market are and this market's quality is not equivalent to the efficiency of price discovery. In contrast, our model isolates information sources of price adjustments.

Hasbrouck (1993) proposes a decomposition of observed price into efficient price plus the pricing error which is a difference between actual price and efficient price. He assumes that the pricing error term has a constant volatility and uses a one standard deviation of the pricing error as a summary measure of market quality. The author conducts analysis using a structural vector moving average (VMA) model for stock's returns based on NYSE transactional data. He also addresses the fact of elevated volatility of returns for beginning and end of trading by providing separate estimation of pricing error standard deviation for midday, first half hour and last half hour sub-samples. His findings show that a standard deviation of pricing errors is higher at the beginning, and to a lesser extent at the end of the trading session. However, the weakness of this approach is that it requires additional restrictions to resolve VMA identification problem, while the state space methodology is less restrictive and provides straightforward estimation of unobservable price and technical volatility (e.g. volatility of the pricing errors).

To resolve the problem of unobservable efficient prices, most research papers focus on cointegration models which assume that multiple market prices for securities share a common implicit efficient price. In other words, this approach suggests that trading prices for the same security from different trading venues are not expected to drift far apart from each other so the difference between them should be stationary.

For example, Hasbrouck (1995) suggests using a price discovery measure such as the information share within a cointegration framework in a multiple markets environment. He defines the information share associated with a particular market as a proportional contribution of that market's innovations to the common efficient price innovation. The information share is based on the common permanent component of all the market prices and is a relative measure that allocates information to the different markets. Harris, McInsh, and Wood (2002) is another example of study that introduces alternative measure of price discovery: the component share. The component share is a weighted average of market's observed price. However, there has been a substantial confusion about the interpretation of both measures because they are defined in terms of markets reduced form innovations from a fitted vector error correction model.

Furthermore, Yan and Zivot (2004) show that the information and component shares say little about the dynamics of price discovery because they only depend on contemporaneous impacts from the structural innovations. Yan and Zivot suggest a structural price discovery cointegration model to assess the dynamics of price discovery based on the speed at which market prices adjust to news about fundamental values and the magnitude of pricing errors. Specifically, price discovery is assessed based on impulse response functions of the market's price to a standardized information event-one unit change in the efficient price of the security. The time path of the price adjustment to the unit permanent shock measures market's price discovery speed, and the magnitude of sum of mispricing errors during the price discovery determines the market's efficiency of price discovery. Although this methodology proposes a theoretical approach that sheds light on the process of price discovery, it is not a convenient tool in terms of practice. Implementation of this analysis requires identification of the price structural moving average model and computation of its impulse response functions.

Empirical literature on price discovery in a single market suggests a variance ratio approach. Specifically, it compares variance ratio of open-to-close and close-to-open returns (Jones, Kaul and Lipson (1994)). Since transactional prices are noisy proxies for unobservable efficient price due to trading friction, variance ratio analysis artificially inflates price discovery within a trading day. This is illustrated by studies that show that returns based on open-to-open prices are approximately 20% more volatile than those based on close-to-close prices (Amihud and Mendelson (1987), Foster and George (1996)). Another criticism of variance ratio methodology is that it ignores contemporaneous correlation (Ronen (1997)).

Our methodology is in spirit of MKS (2007). It proposes an approach based on a state-space model that allows for data smoothing so that temporary microstructure noise can be separated from a long-term trend that is attributed to news about fundamental values. As a result, this approach provides smooth estimates of an unobservable efficient price based on the entire sample. It is an efficient tool that accounts for noise that is attributed to short-term trading friction and provides an unbiased minimum error variance estimator conditional on observations.

The state-space approach has been successfully used in other studies related to price discovery in securities market. For example, Amatatsu and Baba (2007) use a state-space methodology to investigate the relative role of price discovery between two currency swaps: cross-currency basis swap and FX swap on the Yen/US dollar exchange rate. Schirm (2004) applies the state-space approach to assess price discovery for synthetic CDOs (collateralized debt obligations).

Price discovery is usually discussed within the framework of an asymmetric information approach or divergent expectations. The main premise of the information asymmetry approach is that it assumes that there are informed traders in a market who possess private information and trade based on this information. Thus, in a market with asymmetrically informed agents, trades convey information and cause a permanent impact on security prices. Hasbrouck (1991) shows that the impact is a positive and concave function of the trade size. Moreover, he argues that this impact results from the unexpected component of the trade, e.g. the trade innovation. Buy orders convey good news and drive ask prices up, while sell orders convey bad news and push bid price down. The larger the size of the order, the larger its impact on prices. Kyle (1985), Easley and O'Hara (1987), and Glosten (1987) provide extensive theory that analyzes market maker's exposure to informed traders. The theory yields two empirical facts: first, the asymmetry is positively related to the spread, and second, that the asymmetry is positively related to the price impact of trades.

An alternative approach assumes that agents form divergent expectations about share valuation based on publicly available information. Agents valuations differ because they make investment decisions based on a large, complex and imprecise information set. It has been established in the academic literature that heterogeneous expectations effect equilibrium prices (Chen, Hong, Stein (2001), Handa, Schwartz, Tiwari (2003) and Scheinkman and Xiong (2003)). For example, Handa, Schwartz, Tiwari (HST 2003) provide a price formation model in an order-driven (non-intermediated) market where investors have different share valuations.

They show that the size of the spread is a function of the difference in valuation among trades. Specifically, the spread is an inverted U pattern, being high when trading is spread on both sides of the market and being low when trading is concentrated on one side of the market. As noted above, PSW (2010) shows that divergent expectations is a source of accentuated price volatility following public information release. They use the HST price model and adaptive valuations to show that price discovery noise is a major component of the pricing errors in the period when market digests new information.

Market microstructure literature has documented multiple studies in intra-day volatility and volume. Researchers place two U-shaped patterns of trading volume and price volatility into the category of empirical regularity (Andersen and Bollerslev(1997), and Goodhart and O'Hara (1997)). Wood, McInsh, and Ord (1985), and McInsh and Wood (1990) are also among those who show that intra-day volume is significantly higher at the opening and close relative to the activity during midday. Price variability is more pronounced after the opening and before the close regardless of whether it is measured in short or in longer intervals. (Lockwood and Lynn (1990)).

Adamati and Pfleiderer (1988) in their widely cited paper motivate intra-day U-shaped patterns in volume and volatility by strategic behavior of informed and uninformed (liquidity) traders. The main premise of the study is that liquidity traders choose to trade at the open and at the close because they attempt to minimize the adverse selection costs when they trade against informed traders. Therefore, liquidity traders increase their chances to trade with other liquidity traders during the market open and close. This strategic behavior results in clustering at the open and the close and translates into U-shaped patterns for volume and volatility. Sakar and Schwartz (2003) show that volatility is the highest in periods when many buyer-initiated and seller-initiated trades cluster together.

Madhavan (1992) maintains that the observed U-shaped patterns are a result of information asymmetry. Specifically, he suggests that information asymmetry decreases steadily throughout the day as market participants learn from order flow. The author also argues that analyses based on transactional level data for a number of stocks traded on the NYSE shows that dealers' costs increase over the day possibly reflecting the cost of inventory so that bid-ask spread exhibits the U-shaped pattern. A recent study by Tian and Guo (2007) finds L-shaped volatility pattern for Shanghai Composite Stock Index. The authors argue that elevated volatility for the market open is due to accumulated overnight information and the trading halt effect.

M&A announcement are very important news events that cause a significant market reaction to prices of target stocks. It is not surprising that most of such information is released overnight, i.e. after market close. Although the most stressful period for the market is the first 30 minutes of trading (Ozenbas et al. (2002)) when the market starts digesting the overnight news revealing increased trading volume and volatility, we analyze the period from 10:00 A.M. to 3:30 P.M.. This approach allows us to investigate whether price discovery following significant news is a protracted process while mitigating heteroscedasticity in the data due to the volatility smile.

As noted, the premise of this dissertation is that accentuated volatility after M&A announcements is attributed to price discovery noise. We assess the effects of non-instantaneous price discovery around M&A announcements and their contribution to the pricing errors.

Chapter 3. Divergent Expectations vs. Asymmetric Information Environment

As we mentioned above, the literature documents evidence on significant price changes, increases in trading volume and changes in the spread around merger announcement. Significant price changes are the result of protracted pressure from order imbalances for target stocks. The protracted price pressure from order flow signals more one-sided trading around M&A announcements. SS (2009) define market sidedness as a new liquidity measure that is the correlation between the number of buyer initiated and seller initiated trades in an interval. The authors argue that market sidedness reflects divergence or convergence in beliefs. For example, trading motivated by homogeneous or heterogeneous beliefs triggers high volume and volatility but the former results in one-sided market and significant price pressure whereas the latter results in two-sided market with low price impact.

SS (2009) argue that the absolute order imbalances that are defined as the absolute difference between the number of buy-triggered and sell-triggered orders normalized by the total number of trades in an interval is an alternative measure of market sidedness. In our study we use the absolute order imbalances in one minute intervals and the autocorrelation of order flow as two major factors that determine a market sidedness. Large absolute order imbalances would imply more one sided trading in one minute intervals. High autocorrelation of order imbalances would signal that trading concentrates on one market side for periods longer than one minute. SS (2009) find a one-sided trading around corporate restructure announcements including M&A deals.

In our analysis of price behavior around M&A announcements we expect to find more one sided markets, meaning highly correlated and large absolute minute-by-minute order imbalances. We also expect to detect a significant price impact in one minute intervals as a result of persistent pressure from order imbalances in one direction.

In "no-news" sample we expect to observe the market in its natural state, i.e. being two-sided, meaning that the presence of buyers and sellers on the market is roughly equal. Convergence in beliefs that is reflected in convergence of sidedness opens the door to herding among investors which potentially leads to tight spreads. Prior work documents significant price run-ups for more than a week around M&A announcements. With this in mind, we infer that price discovery is a protracted process and that it takes a market awhile to make a transition from its one two-sided state with the established consensus value of share to a new one based on a takeover announcement. As we discussed above, we expect to find a one sided market in its transition from one price equilibrium to another one. This implies that we expect to find a persistent trading activity on one side of the market during several days around M&A announcement.

Whether strong price pressure from one-sided order flow results in market over or undershooting to M&A news is a question that is answered empirically in this study. As we already discussed, there are many factor such as magnitude, precision and dissemination of information that effect a market's reaction to news.

Before doing empirical analysis, we address an important question about the environment that can provide a comprehensive explanation to the expected market one-sidedness around M&A announcements. There are two approaches discussed in the microstructure literature: asymmetric information and divergent expectations with adaptive valuations.

The asymmetric information environment (Admati and Pfleiderer (1988) and Kyle

(1985)) suggests homogenous expectations of equally informed market participants. The standard asymmetric information models include three types of traders: informed traders who have the same expectations about stock's underlying value, uniformed liquidity traders, and noise traders. The latter trade on noise taking it as information. Liquidity traders trade for cash flow related reasons. The models with the three types of participants and homogeneous expectations of the informed traders result in a unique price equilibrium that is no path-dependent. According to these models, trading exists due to the inclusion of liquidity and noise traders.

In contrast, with divergent expectations and adaptive valuations (PSW 2010), investors posses the same information about the underlying stock's value but interpret it differently. Furthermore, investors are free to update their expectations by observing the overall color on the market, and are influenced by the trading decisions of others.

On the one hand, if trades are based on asymmetric information, we expect informed traders to place orders on one side of the market. Moreover, according to the information asymmetry theory, we should expect wider bid-ask spreads if trading is based on asymmetric information. In this case the wider bid-ask spread should manifest the adverse selection costs. In contrast to this assumption, we expect to find a tighter spread around M&A announcements as a result of competitive pressure among agents. Interestingly, Adamati and Pfleiderer (1988) argue that the effect on the adverse information component depends on the degree of competition between informed traders. They show that competition between traders increases if all traders receive identical signals and this increase in competition reduces the adverse information component even if the number of informed traders increases. Even so, can the asymmetric information approach offer a comprehensive explanation of a price discovery process?

We believe that the divergent expectations environment with adaptive valuations provides a more realistic and flexible framework. First, the assumption of homogeneous expectations of informed market participants proposed in the asymmetric information models is a considerable simplification of the reality. Information sets are enormously complex and large. Quantitative models that are used by large institutions to process the information may differ due to innovative research ideas and approaches focusing on different information drivers. This translates into different assessments and disagreements about share values. Schwartz (2008) argues that different analysts' recommendations, short selling, and institutional block trades on both sides of the market are indicators of the divergent expectations of agents.

Second, the asymmetric information approach implies that there will be no trading in the absence of liquidity and noise traders since informed traders who presumably have the same expectations will never trade with each other. This raises a question about the robust operation of a financial market in periods when the proportion of liquidity and noise traders drops.

Third, the classification of agents on the three types is not a clear concept. How can we clearly disentangle between information and liquidity volume? How do we make sure that liquidity trades are based on the idiosyncratic cash flow needs net of effect of information? Can we define with any precision the motives of trading for noise traders? The asymmetric information approach does not provide answers to these questions. Furthermore, this framework views a financial market as an environment where the underlying value of a security is predetermined by the homogeneous expectations of informed trades.

In contrast, divergent expectations with adaptive valuations offer a more realistic approach. It introduces a learning behavior of agents. The adaptive valuation mechanism is a natural interaction process among market participants. Agents adapt their valuations by observing what others are thinking and doing. Farmer and Lo (1998) stressed that the most promising directions of research is "to view financial markets from a biological prospective, specially, within an evolutionary framework, markets, instruments and investors interact and evolve dynamically". The desire to build financial theories based on more realistic assumptions suggests viewing a financial market as a coevolving ecology of trading strategies. The adaptive valuation mechanism is meant to capture the complex learning behavior of agents. Therefore, the process of trading itself affects investor valuation of share values. Moreover, agents are free to produce private information by further processing publicly available information to gain more insights into a stock's valuation. Price discovery becomes a complex dynamic process.

We propose the following price behavior following M&A announcements based on divergent expectations environment with adaptive valuations. Participants receive new M&A information and start processing it to form their expectations about the underlying stock's value. In an attempt to mitigate market impact, agents slice and dice their orders. This slicing and dicing contributes to autocorrelation in order flow. Furthermore, participants observe what others are thinking and doing to adapt their expectations about share value. Adaptive valuations result in correlated investment signals and lead to more autocorrelation in order flow. Therefore, gradual convergence in beliefs translates into convergence of market sidedness. In turn, pronounced and highly persistent market one-sidedness is expected to cause a significant price impact. Convergence in beliefs imply competitive pressure on investors that results in a decreased spread. Our expectation of the decreased spread is consistent with HST (2003) who suggested that the increased spread for one sided market and decreased one for more two-sided trading.

So far we discussed expected price behavior around M&A news and the environment that can provide an explanation for this behavior. In the next chapter we estimate the state-space model to test our assumptions about price adjustments around M&A announcements.

Chapter 4: The Model

4.1. The Unobserved Efficient Price and Order Imbalances

Methodology-wise, this dissertation relates to MKL (2007). The main difference with the MKL (2007) model is that this study proposes a state-space model that is based on the return-order imbalance relation rather than solely on price dynamics. The market microstructure literature, for example Chordia and Subrahmanyam (2002, 2006), argue that order imbalances play a key role in a price dynamics and provide an additional explanatory power for stock's price beyond volume. We suggest a two dimensional observation vector that consists of stock's price and an aggregate order imbalance measure over a time interval.

The order imbalance measure over a time interval is the difference between the total buy orders and sell orders over this time interval normalized by the total number of trades. We construct order imbalance measures from transaction and quotation data using the Lee and Ready trade classification algorithm. Of course, there is inevitably some trade classification error so the resulting order imbalances supply noisy information about true, though, unobservable order flow. We use these constructed measures as proxies for the unobservable order imbalances flow.

Following state-space terminology, our model specifies an unobservable state vector as consisting of the efficient price p_t and a true, though, an unobservable value of order imbalances x_t. Similar to MKL (2007) and Hasbrouck (1993), we model efficient price as a random walk driven by innovations e_{1t} that impound new information about the fundamental value of the underlying security. We assume that these innovations have a time-invariant volatility σ_1.

Previous studies have document persistency in order flow. For example, Bouchard et al. (2004), Chordia et al. (2006) and Easley et al. (2001). The main explanation for this finding is that traders slice and dice their orders to minimize market impact. Based on this fact, we specify the unobservable order imbalances x_t as an autoregressive process driven by innovations e_{2t} with a time-invariant volatility σ_2. Thus, the model equations are given

$$p_{t+1} = p_t + e_{1t}$$
$$x_{t+1} = \varphi x_t + e_{2t} \qquad [3]$$

where $E[e_{1t}] = 0$, $E[e_{1t}^2] = \sigma_{e1}^2$, $E[e_{2t}] = 0$, $E[e_{2t}^2] = \sigma_{e2}^2$, $E[e_{1t}, e_{2t}']$.

In contrast to innovations of the efficient price e_{1t} that are solely associated with news, innovations e_{2t} that drives dynamics of order flow in the model equation can be attributed to both information and a demand for liquidity. Moreover, since the information set is very complex, it is very difficult for the diverse investors to fully comprehend it. Andrade, Chang and Seasholes (2008) maintain that a significant amount of trading imbalances reflect uninformed trading. Also, Lee (1992) finds that investors do not place orders according to announced information. This allows us to assume independence of innovations in the efficient price and order flow.

4.2. The Observation Model of Price and Order Imbalance: A Discussion of Imperfect Price Discovery Effects

The actual prices differ from the efficient prices due to implicit costs associated with bid-ask bounce, market impact, momentum trading and price discovery. The primary goal of this dissertation is to study a price discovery process following M&A news release and reveal imperfect price discovery effects. This implies focusing on the price impact of order flow triggered by information. In response to new information about the underlying security, market participants collectively discover the new consensus value of the stock by placing their orders that reflect their opinion about the fair value. This results in the formation of information triggered order flow that creates a pressure on a stock's price and leads to price adjustments to news.

However, the process takes time. Price does not adjust instantaneously to a new level based on news due to friction factors. To avoid adverse market impact, market participants tend to slice and dice their order and thus cause a delay in price discovery process. It takes time for the divergent expectations of investors to converge through an adaptive valuation mechanism. Following MKL (2007), we take midquotes m_t as the best proxies for the unobservable efficient price since they are not affected by the bid-ask bounce.

The pricing error which is the difference between the midquote m_t and the efficient price p_t is associated with imperfect price discovery factors such as price impact and market over/under reaction to news and a residual term η_{1t}. Price impact in our model is captured by a factor β from contemporaneous order imbalances x_t that are associated with slicing and dicing, liquidity events and technical momentum trading. This study does not premise on distinguishing between groups of investors who cause the price impact. Although previous studies indicate that order flow is a long memory process, we choose to use the contemporaneous order imbalances in our model as they appear to cause the largest price impact. Note that β captures only the linear price impact from the contemporaneous order imbalances.

Our model allows for potential market over/under reaction to information which is discussed and proposed by Amihud and Mendelson (1987). Market over/under reaction to news is modeled as a price reaction α to the efficient price change $p_t - p_{t-1} = e_{1t}$. We cannot assume ex-ante if the price impact results in market over or under reaction to news. The result depends on how agents place their orders in response to release of new information. We answer this question by estimating market over or under reaction empirically.

The residual term η_{1t} represents a part of pricing error that has not been fully captured by the price impact from contemporaneous order imbalances or market over/under reaction to news. Price impact is a nonlinear concave function of order imbalances (Plerou et al. 2002). Since our model estimates a linear price impact of contemporaneous order imbalances, the residual term reflects the pricing errors that are associated with nonlinearities in the price impact. The residual term also contains price effects of higher order lag order imbalances. The error term also captures the pricing errors due to the discrete price grid.

As we discussed above, the constructed Lee and Ready order imbalances i_t from transaction and quotation data represent noisy information about true but unobservable order imbalance. The difference between the observable and unobservable order flow is due to trade classification errors. Thus the observation equations are given

$$\begin{aligned} \ln m_t &= \ln p_t + \alpha(\ln p_t - \ln p_{t-1}) + \beta x_t + \eta_{1t} \\ i_t &= x_t + \eta_{2t} \end{aligned} \qquad [4]$$

where $E[\eta_{1t}] = 0$, $E[\eta_{1t}^2] = \sigma_{\eta 1}^2$, $E[\eta_{1t}, e_{1t}'] = 0$, $E[\eta_{1t}, e_{2t}'] = 0$, $E[\eta_{2t}] = 0$,

$E[\eta_{2t}^2] = \sigma_{\eta 2}^2$, $E[\eta_{1t}, \eta_{2t}'] = 0$, $E[\eta_{2t}, e_{1t}']$ =0 and $E[\eta_{2t}, e_{2t}']$ =0.

We take a similar approach to MKL (2007) and consider $nx1$ vector p_t which contains the unobserved efficient prices of n stocks at day t. Order imbalance, midquotes, innovations and error terms are also $nx1$ vectors. The model assumes uncorrelated error terms e_{1t} and η_{1t}. This assumptions seems to be counter intuitive since large innovations in the efficient price may lead to inaccurate price discovery with large pricing errors including η_{1t}. This would be impossible to relax this assumption as the model would become underidentified (Hasbrouck (1993)).

4.3. Casting the Model to the Standard (Gauss-Markov) State Space Form.

In this section we present our model that consists of transition equation [3] and observation equation [4].

$$p_{t+1} = p_t + e_{1t}$$

$$x_{t+1} = \varphi x_t + e_{2t}$$

$$\ln m_t = \ln p_t + \alpha(\ln p_t - \ln p_{t-1}) + \beta x_t + \eta_{1t}$$

$$i_t = x_t + \eta_{2t}$$

where $E[e_{1t}] = 0$, $E[e_{1t}^2] = \sigma_{e1}^2$, $E[e_{2t}] = 0$, $E[e_{2t}^2] = \sigma_{e2}^2$, $E[e_{1t}, e_{2t}']$ and

$E[\eta_{1t}] = 0$, $E[\eta_{1t}^2] = \sigma_{\eta 1}^2$, $E[\eta_{1t}, e_{1t}']$=0, $E[\eta_{1t}, e_{2t}']$=0, $E[\eta_{2t}] = 0$, $E[\eta_{2t}^2] = \sigma_{\eta 2}^2$,

$E[\eta_{1t}, \eta_{2t}']$, $E[\eta_{2t}, e_{1t}']$=0 and $E[\eta_{2t}, e_{2t}']$=0.

in the standard Gauss-Markov state space form:

$$y_{t+1} = A_t(\theta) y_t + Q_t(\theta)\varepsilon_{1t}$$

$$z_t = H_t(\theta) y_t + \varepsilon_{2t}$$

where $E[\varepsilon_{1t}] = 0$ and $E[\varepsilon_{1t}\varepsilon_{1s}'] = T_t(\theta)$ for $s = t$ and 0 otherwise and

$E[\varepsilon_{2t}] = 0$ and $E[\varepsilon_{2t}\varepsilon'_{2s}] = R_t(\theta)$ for $s = t$ and 0 otherwise, and $E[\varepsilon_{1t}\varepsilon'_{2s}] = 0, \forall t, s$ and $E[y_0\varepsilon'_{2t}] = 0, \forall t$.

The model of interest can be casted in the state space form by denoting

$$y_t = \begin{bmatrix} \ln p_t \\ x_t \\ \varepsilon_{1t-1} \end{bmatrix} \quad z_t = \begin{bmatrix} \ln m_t \\ i_t \end{bmatrix}$$

with $3nkmx1$ y_t state vector, $2nkmx1$ observation vector, n number of stocks, k number of days in a sample and m number of intraday time intervals. The state space disturbance vectors are specified as

$$\varepsilon_{1t} = \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \quad \varepsilon_{2t} = \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix}$$

The vector of parameters is

$$\theta = \begin{bmatrix} \varphi \\ \alpha \\ \beta \\ \sigma_{e1} \\ \sigma_{e2} \\ \sigma_{\eta 1} \\ \sigma_{\eta 2} \end{bmatrix}$$

The state space matrices are

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \varphi & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad H = \begin{bmatrix} 1 & \beta & \alpha \\ 0 & 1 & 0 \end{bmatrix}$$

$$T = \begin{bmatrix} \sigma_{e1}^2 & 0 \\ 0 & \sigma_{e2}^2 \end{bmatrix} \quad R = \begin{bmatrix} \sigma_{\eta 1}^2 & 0 \\ 0 & \sigma_{\eta 2}^2 \end{bmatrix}$$

Chapter 5: Data and Descriptive Statistics

5.1. A Description of the Data

The dataset used for this dissertation consists of trade and quote data from the Transaction and Quotes (TAQ) Database of the NYSE. The data are from January 2, 2004 to December 31, 2008 for 53 NYSE stocks that went through major US corporate restructuring deals in this period. The data on major M&A events with names of acquire and target firms, the status of the deal, date and time of announcement is taken from Bloomberg. We choose target stocks to analyze price discovery effects around M&A announcements since they are expected to be more sensitive to such releases. The list of stocks can be found in Appendix B.

In order to examine price discovery around M&A announcements we construct a "Before" and "After" test samples that consist of the two days before and after M&A news respectively. Specifically, for the "After" sample we choose the day of merger announcements and following day. All of the M&A announcements in our sample were made after market close meaning that we choose the next trading day as the day of takeover announcements. Prior literature indicates significant price changes of target symbols during at least a weekly period around M&A news. We concentrate on a shorter period and consider the closest two days before and after M&A news release to capture more immediate effects of news on order flow and price.

In order to make any conclusions about price discovery effects around M&A announcements we need to contrast the results using a "Control" or "No-news" sample that is constructed to minimize the possible magnitude of news. Following SS (2009), we remove the 2 days before and 2 days after quarterly earnings reports and major macroeconomic news. Previous studies (Fleming and Remolona (1999)) identify Core Consumer Price Index (CPI), Producer Price Index (PPI) and announcements on Employees Nonfarm Payroll as the three major macro releases that have the most significant market impact. Dates of macro announcements are scheduled for release for specific days and we take these dates from Bloomberg. Information on dates of earnings reports are available from I/B/E/S database.

Previous studies suggest persistent volatility of the target stocks after M&A news release. In order to eliminate this volatility effect, we construct the “Control” sample from days preceding M&A announcements. The previous studies indicated a significant surge in daily trading volume and significant daily net buying orders for target symbols around -14 day. We choose the days that are before -14 day for the “Control” sample. To further mitigate any news impact, we exclude days with the top 30% percentile of absolute value of excess close-to-close returns. In other words, we suggest removing high values of absolute close to close stock returns vs. market by using a comparison of individual stock with the S&P500. A similar methodology has been proposed by SS (2009).

The TAQ data is not error filtered. We apply the following preliminary filters to clean the TAQ data from potential errors: any non positive trade prices and quotes were eliminated. Any bid (ask) quotes with negative spread or bid (ask) quotes that change from the previous bid (ask) quote by more than $10 were removed from the data. Trade or quote prices that are outside of regular trading hours from 9:30 A.M. to 4 P.M. are removed. These filters removed approximately 3% of the data.

After this filtering, we segment the TAQ data for each stock and each of the three samples into one minute intervals. We create the following set of variables:

1. Mid-quotes
2. Order imbalances
3. Proportional spread

4. Volume (number of shares traded in the interval)
5. Number of trades in the interval
6. The difference between buy triggered and sell triggered orders
7. The difference between number of shares bought and sold in the interval
8. Volatility (the ratio of the highest to the lowest price in the interval minus one)

Mid-quotes are the average of the bid and ask prices and the proportional spread is the ratio of the difference between the ask and bid prices over the mid-quote expressed in basis points. The volatility is calculated as the ratio of the highest to the lowest price in the interval minus one and expressed in percents.

Order imbalance is the difference between the number of buyer initiated trades and seller initiated trades normalized by the total number of trades in the interval. The order imbalances are constructed from the TAQ data using the Lee-Ready (1991) trade classification algorithm. We compare the trade price with the most recent bid (ask) price and define trades above the midpoint of the bid-ask spread to be buy-triggered orders and trades below the midpoint of the spread to be sell-triggered orders. If the price is equal to the mid-quote, then trades that take place on up tick/down tick is buy/sell. If there is no price movement then we move back to the prior price movement and repeat the same comparison procedure. The algorithm has been applied to each transaction in each of the three samples. After assigning the trade direction, we define the difference in the number of bought and sold shares using the transaction data.

Finally, the “After” sample comprises 32781 one minute intervals. The “Before” sample consists of 32159 one minute intervals and the “Control” sample has 33247 one minute intervals.

5.2. Descriptive Statistics of Major Variables

This section provides the descriptive statistics of the constructed variables for each of the test samples. We are interested to obtaining insight into the relationships among the constructed variables for the time periods around M&A announcements and contrast the results with "No-news" sample. We begin an analysis by presenting the average and median statistics for the proportional spread, volume, number of trades, the difference between number of buyer-initiated trades and seller-initiated trades, the difference between shares bought and sold and volatility.

SS (2009) use the absolute order imbalances as an alternative measure of market sidedness to the one that is measured as the correlation between the number of buy-triggered and sell-triggered orders in time intervals. Low absolute order imbalances indicates more two-sided market in one minute interval whereas high absolute order imbalances signal more one-sided trading.

Though previous studies find significant price run-ups of target stocks before M&A announcements, evidence on price adjustments on the day after M&A news provides mixed results. As we discussed above, the recent studies (Daouck and Li (2009)) indicate different investor behavior in days following M&A news: institutional investors revert their positions in the target stocks after M&A news except for brokerage firms that continue to buy shares in target stocks to speculate on the final deal.

To obtain more details into a direction of price adjustment before and after M&A announcements in our sample of stocks, we construct close to open returns for each test samples using close price of the second day and open price of the first day in each sample. While the mean of returns in the "Before " sample indicates significant price run-ups of target stocks before M&A announcement, the mean of price changes after merger news is statistically insignificant. After examining price returns in the "After" sample, we separate them into two groups: stocks with price run-ups and those with downward price trend after M&A announcements. In Table 1 we provide the mean of the returns in the pre- and post-announcement periods separated in two groups depending on a direction of price adjustments following merger news.

Additionally, we need to clarify to what extent price adjustments in target symbols are driven by market conditions rather than M&A news. To address this issue, Table 1 also provides the mean of market returns from the second day close to the first day open for the "After" , "Before" and no-news days. Our findings indicate that price changes in target stocks in the post- and pre-announcement period are not attributed to market movements but associated with M&A news. No statistically significant difference between the means of the target and market returns is observed in the no-news days.

We suggest coupling the absolute imbalance metrics with the autocorrelation of the order flow to better capture market sidedness. The magnitude of the absolute order imbalances indicates how strong asymmetry in the order flow whereas the autocorrelation shows how persistent this asymmetry. Previous findings of significant price changes of target stocks around M&A announcements indicate that we expect a more one-sided market (i.e. large and highly autocorrelated order imbalances) around takeover news release.

We also expect trading after M&A news release to reveal high trading volume and trading activity in terms of the number of trades in one minute intervals. In turn, we expect high volume (trading activity) to be associated with elevated price volatility. Finding increased volume and volatility along with pronounced one-sided market in the "Before" sample can be indicative of price adjustments to information prior to public announcement. In contrast, we expect lower volume (trading activity), price volatility and order imbalance asymmetry in trading patterns in no-news days.

The trading day from 10 A.M. to 3:30 P.M. is divided into one minute intervals. The variable VOLUME is the number of total shares traded in the interval. NUM is total number of trades in the interval. We capture one of liquidity facets by SPREAD, the proportional spread ratio of the difference between ask and bid prices to the quote mid-point over a one minute interval, presented in basis points. Volatility, HILO, is the ratio of the highest to the lowest price in the interval minus one expressed as percent. The variable DIFF_NUM is the difference between number of buyer-initiated and seller-initiated trades. The variable DIFF_SHARES is the difference between number of buyer-initiated and seller-initiated shares. Order imbalance, OIM, is DIFF_NUM normalized by the total number of trades, NUM. All these variables are constructed for the “Before”, “After” and “Control” samples for 53 target NYSE stocks that have been reported in major US corporate restructuring news from January 02, 2004 to December 31, 2008.

Additionally, Figure 1 shows minute by minute volatility in the first 30 minutes of trading from 9:30 A.M. to 10:00 A.M. for the test and control samples. Volatility in the first 30 minutes of a trading day reflects the immediate price impact of overnight news on stock’s price. The graphs indicate the highest one minute volatility in the first 30 minutes of trading in the days following M&A news and the lowest volatility level in the no-news day. The average one minute volatility in the first half hour of the first day after M&A announcement is 18 % . The second day after takeover news shows the average volatility of 16.5 %. Large standard errors for one minute volatility in the post announcement period prevents us from establishing statistically significant difference in the means between the first and second days. In comparison, the average one minute volatility in the first half-hour of the days before the M&A announcement is 14%. No-news period reveals that the average one minute volatility from 9:30 A.M. to 10 A.M. is 12 % . The differences in the means of the volatilities between the days in “After” and no-news periods are statistically significant at the 5% level of confidence.

Ozenbas et al. (2002) examine half-hour volatility for five markets including NYSE, Nasdaq, London Stock Exchange, Euronext Paris and Deutsche Borse in 2000. The authors find a substantial volatility spike in all five markets for the first half hour and argue that this is attributable to price discovery which extends into and perhaps beyond the first half-hour interval. This dissertation focuses on analyzing the price behavior between 10 A.M. and 3:30 P.M. in two days after M&A announcements and therefore, examines if price discovery is a protracted process that extends to at least two days after M&A announcements.

Table 2 presents the descriptive statistics of VOLUME, SPREAD, HILO, the absolute difference of the number of buyer-initiated and seller-initiated trades ABS_DIFF_NUM, the absolute difference of the number of shares bough and sold ABS_DIFF_SHARES and the absolute imbalance AOIM around M&A news release and in no-news days. We compare the mean and median values using the Wilcoxon z statistics between days in the test samples and “No-news” sample. Bold entries indicate a statistically significant difference at the 5% confidence level in the means or medians between the test samples and the control sample. We find significantly higher mean and median of volume and number of trades in the “After” sample vs. both the “Before” and “Control” samples. The average volume in the one minute interval for days after M&A announcements is a factor 6 higher compared to the average volume in days without news. The average volume in the post-announcement periods is a factor 3 higher compared to the average volume in the pre-announcement period. Also, the average number of trades is a factor 2 higher in the "After" sample compared to no-news days and a factor 1.5 higher vs. the "Before" sample. Our findings of increased volume and trading activity around M&A announcements are consistent with a sizable literature suggesting that trading around news event is associated with a significant surge in volume and number of trades.

The absolute difference in number of shares between buy and sell orders is a factor 6.3 higher in "After" sample compared to the "Control" and 3.3 higher compared to "Before" sample. However, we do not find a statistically significant difference between the absolute values of order imbalances in all samples. This is attributable to the fact that the high frequency order imbalance metrics is very noisy, and an analysis of order imbalances requires precaution in a statistical approach to eliminate the noise in the data.

The proportional spread is the smallest in the "After" sample. SPREAD in no-news days is a factor 1.8 higher compared to the days following M&A announcements. This difference is statistically significant at the 5% level of confidence. We find no statistical difference between the means of the proportional spreads in days before M&A news release and no-news days. The mean and median of HILO in the "After" sample are larger compared to the "Control" and "Before" sample. The differences in the means and medians of HILO between the post - announcement and no-news period are statistically significant at the 5% level of confidence.

In order to shed more light on the dynamic behavior of the major variables around M&A news, Table 3 shows the means and medians of autocorrelation patterns for VOLUME, NUM, SPREAD and OIM. Our analysis reveals that autocorrelations in all these variables are more pronounced in the post-announcement days vs. the control sample and the pre-announcement period. The difference in the means and medians of the autocorrelations in volume, number of trades, the proportional spread and order imbalances between the “Control” and “After” samples is significant at the 5% confidence level. In contrast, no statistically significant difference is observed in the medians of the autocorrelation coefficients between the “Before” sample and no-news days. This finding indicates high persistency in volume, trading activity, liquidity, volatility and order flow in the “After” sample.

We presume that significantly higher correlations in the “After” sample are attributable to a price discovery process. The market reacts to public announcement of M&A news by increased trading volume. In the presence of new information, agents tend to slice and dice their orders more to hide market impact. Moreover, agents with divergent expectations about a stock’s value can adjust their valuations by observing what others are thinking and doing. Thus, market participants may place their orders based on correlated signals (i.e. by observing the transaction prices). This may create additional autocorrelations in the order flow. In the next chapter we examine if trading after M&A announcements are more informative and associated with price discovery.

Chapter 6: Estimation of the State-Space Model

6.1. Parameter Initialization

The state-space algorithm starts with a feasible choice of the parameter vector $\theta = [\varphi \quad \alpha \quad \beta \quad \sigma_{e1} \quad \sigma_{e2} \quad \sigma_{\eta 1} \quad \sigma_{\eta 2}]'$ and corresponding state vector y_0 with variance-covariance matrix P_0. As we discussed above, if the distribution of the state vector $y_t = [\ln p_t \quad x_t \quad \varepsilon_{1t-1}]'$ is not known, it is reasonable to represent y_t as having a diffuse prior density, that is, fix y_0 at an arbitrary value and let $P_0 \to \infty$. We set up the initial value of the state vector $y_0 = [0 \quad 0 \quad 0]'$ and let $P_0 \to \infty$ for each of three samples: the "Before", "After" and "Control".

In order to initialize the first component φ of the parameter vector θ, we suggest using the estimates of the autocorrelation coefficients from the first order autoregression models based on the constructed order imbalance measures (OIM) i_t. The first order autoregression models of OIM are given below:

$$i_{t,s} = \rho_s i_{t-1,s} + \xi_{t,s}$$

where ρ is autocorrelation coefficient, ξ is normally distributed noise term and s is indicator that takes values from 1 to 3 for the "Before", "After" and "Control" samples respectively.

Before running the autoregression analysis, we test the OIM time series for stationarity. We apply the Augmented Dickey-Fuller test (Hamilton (1994)) to each OIM sample to check the null hypothesis that OIM is characterized by a random walk. Table 4 reports Dickey-Fuller t-statistics for the "Before", "After" and No-news samples. The results of the test reject the null hypothesis in favor of the alternative hypothesis that OIM are stationary time series.

Table 5 displays the estimates from autoregression analysis. The autoregression coefficient for order imbalances in the post announcement period is the largest among three samples, implying a greater degree of convergence in expectations of share value among agents in a period following M&A announcements when the market is in transition to the new consensus value. It is not surprising that for all three samples we find a small explanatory power about 3-5% of the autoregerssion model for order flow. Constructed one minute order imbalances are extremely noisy measures.

We choose to take a volatility of actual log returns to initialize a volatility of innovations σ_{e1} of the efficient price and dispersion of noise term $\sigma_{\eta 1}$ in the price observation equation. By analogy, we set the initial values of volatilities of disturbances in the state and observed order imbalances to be equal to the volatility of the error terms in the autoregressions. The estimates of the volatility of log returns based on mid-quotes and error terms in the OIM autoregressions are reported in Table 6. Price impact β and market over/under reaction α are unknown ex-ante and we assign them with zero values. Finally, the initial vectors of parameters are given below:

$$\theta = [\varphi = 0.187 \quad \alpha = 0 \quad \beta = 0 \quad \sigma_{e1} = 0.037 \quad \sigma_{e2} = 0.619 \quad \sigma_{\eta 1} = 0.037 \quad \sigma_{\eta 2} = 0.619]'$$

for the days before M&A announcements,

$$\theta = [\varphi = 0.219 \quad \alpha = 0 \quad \beta = 0 \quad \sigma_{e1} = 0.030 \quad \sigma_{e2} = 0.054 \quad \sigma_{\eta 1} = 0.030 \quad \sigma_{\eta 2} = 0.054]'$$

for the days following M&A announcements and

$$\theta = [\varphi = 0.186 \quad \alpha = 0 \quad \beta = 0 \quad \sigma_{e1} = 0.029 \quad \sigma_{e2} = 0.026 \quad \sigma_{\eta 1} = 0.029 \quad \sigma_{\eta 2} = 0.026]'$$

for no-news days.

6.2. Parameter Estimation

In this section we report and discuss the estimated parameters. The parameters are estimated using the likelihood function based on the prediction errors from the Kalman filter for the proposed state-space model:

$$p_{t+1,s} = p_{t,s} + e_{1t,s}$$

$$x_{t+1,s} = \varphi x_{t,s} + e_{2t,s}$$

$$\ln m_{t,s} = \ln p_{t,s} + \alpha(\ln p_{t,s} - \ln p_{t-1,s}) + \beta x_{t,s} + \eta_{1t,s}$$

$$i_{t,s} = x_{t,s} + \eta_{2t,s}$$

where $E[e_{1t}] = 0$, $E[e_{1t}^2] = \sigma_{e1}^2$, $E[e_{2t}] = 0$, $E[e_{2t}^2] = \sigma_{e2}^2$, $E[e_{1t}, e_{2t}']$,

$E[\eta_{1t}] = 0$, $E[\eta_{1t}^2] = \sigma_{\eta 1}^2$, $E[\eta_{1t}, e_{1t}']$=0, $E[\eta_{1t}, e_{2t}']$=0, $E[\eta_{2t}] = 0$, $E[\eta_{2t}^2] = \sigma_{\eta 2}^2$,

$E[\eta_{1t}, \eta_{2t}']$, $E[\eta_{2t}, e_{1t}']$=0, $E[\eta_{2t}, e_{2t}']$=0, $s = 1,2,3$ refers to the “Before”, “After” and “Control” sample and t is one minute interval. Tables 7, 8 and 9 display estimated vector of parameters θ for the days following M&A announcements, before M&A announcements and in days without news respectively.

Our results suggest that in the period following M&A announcements the autocorrelation of the OIM is the highest among three samples. It comprises 0.96 and indicates a highly persistent order flow in days following takeover news. Moreover, the difference between the autocorrelation coefficient of order imbalances in the “After” sample is statistically significant at the 5% confidence level vis-a-vie the “Before” and “Control” samples. The autocorrelations of order imbalance measures in the days before M&A announcements and in no-news days are 0.93 and 0.92 respectively. We find that there is no statistical difference between them at the 5% level of confidence. In order to confirm the stationarity of the estimated order flow series, we ran the Augmented Dickey-Fuller test on them. Table 10 reports Dickey-Fuller t-statistics for the "Before", "After" and no-news samples. The results of the test reject the null hypothesis in favor of the alternative hypothesis that the estimated OIM are stationary time series.

The absolute OIM reveal a significant asymmetry in order flow in one minute intervals in days following merger news. Table 11 shows the mean and median of the absolute OIM for the test and control samples indicating a statistically significant difference in the means and medians between the M&A news. The result also suggests a one-sidedness of the market before merger news, though the asymmetry in the order flow is much weaker compared to the days following merger news. We find that that the difference in the means and medians of the absolute OIM in the "Before" and no-news samples is statistically significant at the 5% level of confidence. Note, that we were unable to detect asymmetry in the absolute order imbalances using the unfiltered Lee-Ready imbalances due to extreme noisiness in the high frequency order flow metrics.

Our finding of a highly persistent OIM in days following merger news is consistent with our previous results showing significantly high autocorrelations in volume, trading activity, proportional spread, the absolute difference between the number of buy-triggered orders (shares) and sell-triggered orders (shares) for these days. Furthermore, we believe that a significantly high autocorrelation of the order flow after M&A announcements is a result of two factors: order slicing and dicing and adaptive valuation mechanism among participants with divergent expectations. In the presence of information that triggers more one-sided trading and therefore, higher market impact, market participants tend to slice and dice their orders even more than in a period without such information. This introduces additional correlation into order flow. Market participants may also observe a persistent order flow on one side of the market and review their trading strategies by placing orders in the direction of order imbalances. This may also enforce autocorrelations in order flow after M&A news releases. A one-sided market indicates that market participants tend to place orders on the same side of the market meaning competition among investors. This competition results in a decreased spread in the two days following M&A announcements.

The results also reveal that the price impact from order imbalances is the largest in the days after merger news. The price impact coefficient in the "After" sample is statistically significant at the 5% level of confidence and it is a factor 6 higher than the price impact before M&A announcements. The price impact in no-news days is small and statistically insignificant at the 5% confidence level. Our results also reveal that though the price impact in days before merger news is much weaker than in "After" period, it is statistically significant at the 5% level.

Our findings lend support to the expected price behavior around merger news. We confirm that highly autocorrelated and predominantly one-sided one minute order flow that stems from highly autocorrelated and significantly increased trading volume in days after M&A announcements creates a significant pressure on stock's price. This pressure from order imbalances results in large price impact.

In contrast, a weaker trading activity and relatively low order imbalances and autocorrelation of order flow in days before merger news are not able to create a strong price impact. The increased price pressure from order imbalances in days preceding M&A announcements may indicate market anticipation of news and signals adverse selection costs meaning that some investors execute at an unfavorable price point within a short interval prior to a substantial price improvement opportunities (Altunata, Rakhlin and Waelbroeck, (2010)).

Our finding of less pronounced price impact in the pre-announcement period is consistent with evidence provided by Gao and Oler (2008). The authors find increased selling activity in target stocks that offsets buying activity. Sellers in the pre-announcement period are rational investors that trade on market overreaction to M&A rumors which in most cases fail to materialize into public announcements. As a result of this selling activity, we observe a smaller correlation in the order flow in days preceding an information event, resulting in a much weaker price impact compared to the days after news.

We find a small and statistically insignificant price impact in no-news days. This is consistent with detected low trading activity and a strong two-sided market during this period. Divergent expectations of agents translate into lower correlations of order flow. In turn, weak correlations in order flow are incapable of building a significant price pressure and therefore, stock's price remains intact in a relatively tight trading range.

Figures 4 and 5 illustrate our findings by showing estimated efficient price and order imbalances for the "After" and "No-news" samples for a single stock (FBF) over a 30 minute trading window. Our results reveal that constructed Lee-Ready order imbalances are very noisy variables. Also, one-sided order flow following news releases indicates convergence in beliefs of participants about a stock's underlying price in the "After" sample. The order imbalances are more correlated in the days after M&A news. In contrast, order flow is predominantly two-sided and less correlated in days without news signaling divergent opinions of the investors. Interestingly, the graphs show a larger deviation of actual prices from the estimated efficient price in days after information event. This finding implies higher implicit trading costs over the period of price discovery. We will examine pricing errors and its implication for efficiency of price discovery in the next section.

As a confirmation of a price discovery process in days following M&A announcements, we find that trading is more informative in the post-announcement period. Following MKL (2007), we measure price discovery - the information flow per unit of time - by the standard deviation of price innovations σ_{e1}. The standard deviation of price innovations reflects the magnitude of fluctuations in the efficient price. Large price fluctuations signal about considerable price adjustments to new information. We find that the standard deviation is the largest in the “After” sample compared to the “Before” and “Control” samples. The post-announcement period is a significant factor 2 more informative than no-news days. No statistically significant difference in the standard deviation of the efficient price in days before M&A announcement and in no-news days is observed.

Interestingly, negative alpha coefficients in all samples indicate a small and statistically insignificant average market under-reaction to M&A news in one-minute intervals. As we indicated above, we find no statistically significant difference in information flow per unit of time between the “Before” and “Control” samples. Hence, it is not surprising to find insignificant market reaction to news in “no-news” days and in the pre-announcement period. However, insignificant average market reaction to news in days after information events requires an additional clarification.

Behavioral finance theory maintains that in financial markets there is a whole chain of investor reactions to an information event. Specifically, it is suggested that, in the short-term, investors tend to delay their buying or selling decisions. As a result, stock’s price under-reacts to news in the short-term. As information diffuses for a while, the market under-reaction is followed by gradual price adjustments. These price adjustments manifest themselves in price momentum. In the long run, this price momentum can lead to price overshooting and subsequent price reversion. There are studies on behavioral model that use different time frequencies for analysis from daily, monthly, yearly returns to intraday returns that reflect price movements over a few minutes.

For example, Hong and Stein (1999) study long-term price returns and argue that information from investors who base their investment decisions on additional research triggered by news announcements transmits slowly into the market causing under-reaction in stock returns. In contrast, agents who base their trades on the observed historical price patterns may extrapolate a price trend and push price away from fundamental value, causing a reversal in stock returns.

Kadiyala and Rau (2002) tested two alternative hypotheses of the investor under-reaction and over-reaction to explain long-run abnormal returns following corporate restructuring news. Specifically, they examine -1 to +1 day returns around cash-financed acquisition, stock-financed acquisitions, share repurchases and seasoned equity offerings and conclude that “investors under-react to short-term information available prior to the event and subsequently under-react to information conveyed by the corporate event”.

In contrast, empirical studies based on intraday price returns document a whole chain of investor reaction to news. For example, Husodo et al. (2009) study price adjustment of major liquid stocks traded on Malaysian Stock exchange over different intraday frequency sampling and find that, on average, prices fully adjust to news in about 30 to 60 minutes after news announcements.

If the whole chain of investor reactions occurs at intraday time intervals, then our finding of insignificant market reaction to news in days after an information event is likely to be a result of averaging of intraday under- and over-reactions to M&A news.

6.3. Pricing Error

The concept of the pricing error has been introduced by Hasbrouck (1993) who defines the pricing error as the difference between the actual price and the efficient price. He proposes to use the standard deviation of the pricing error as the inverse measure of a market's efficiency of price discovery. According to our model, the total pricing error is defined

$$\delta_{t,s} = \ln m_{t,s} - \ln p_{t,s} = \alpha(\ln p_{t,s} - \ln p_{t-1,s}) + \beta x_{t,s} + \eta_{1t,s} \qquad [5]$$

where $s = 1,2,3$ refers to the "Before", "After" and "Control" sample and t is one minute interval.

The price discovery is a non-instantaneous process meaning that stock's price does not immediately adjust to new information. Therefore, we expect higher pricing error after news compared to no-news or before news period. As we mentioned above, Figures 4 and 5 support our hypothesis of the accentuated pricing errors in the post announcement period. The standard error of the residual term η_{1t} is a part of the total pricing error. The estimates of the standard errors of the residual terms for the three samples reveal significantly higher standard deviation $\sigma_{\eta 1}$ of the residual term for the observed mid-quote in the period following M&A information event.

The dispersion of the residual error η_{1t} is a factor 1.6 higher in the "After" sample compared to the "Before" and no-news days. This difference is statistically significant the 5% confidence level. We do not find statistically significant difference in the magnitude of the residual error between the days before M&A announcements and in no-news period.

To validate our hypothesis of the larger total pricing errors in the period after M&A announcements, we examine the total pricing errors obtained from the left hand side of the equation [5] using the estimates of our state-space model. Table 12 summarizes our findings. On average, the dispersion of pricing error is a significant factor 5 higher in days following M&A announcements compared the pre-announcement period. To compare, the standard deviation of pricing errors in the "After" sample is 2% of the mid-quote vs. 0.4% of the mid-quote price in the "Before" sample.

We also find that the standard deviation of pricing error in no-news days is 0.1% and it is statistically insignificant at the 5% level of confidence. All estimates of the dispersion of pricing errors and their differences in the means in the test samples are statistically significant at the 5% level of confidence. Figure 6 shows the pricing errors for one symbol for each of the three samples. Note that our findings suggest the primary role of market impact in the accentuated pricing error after M&A announcements.

Interestingly, trading costs that are due to pricing errors are higher than the spread in the post-announcement period. Note that our methodology excludes the spread component from pricing error by examining the difference between mid-quote and the efficient price. We find that the spread is the lowest in days after merger news compared to the "Before" and no-news sample. In contrast, the standard deviation of the pricing error is the largest in days following M&A announcements. The proportional spread on average is 0.045 % of the stock's mid-quote price, whereas the dispersion of the pricing error is 2% of mid-quote price. For example, if stock's price is $30 then the average trading costs associated with spread over one minute interval are about 1.5 cents. To compare, trading costs due to non-instantaneous price discovery that translates into large pricing errors are 60 cents.

In the no-news period the average spread related trading costs are about 2 cents whereas the pricing error is found statistically insignificant at the 5% level of confidence. In the days before M&A announcements, the spread related trading costs comprise on average about 2 cents. It is low compared to 12 cents of trading costs due to the pricing errors before public announcements of M&A news.

Our findings of a significant contribution of price discovery to pricing error is in line with PSW (2010) suggesting that it is unlikely that a factor such as spread alone can be a sufficient explanation for the magnitude of the short-term volatility. The authors argue that price discovery is a major factor that contributes to volatility surges that follow public news releases.

Chapter 7: Checking Procedures

In this section we perform specification tests using diagnostic analysis on the standardize prediction errors described in Appendix A. We also validate the robustness of the estimated parameters of the state space model.

7.1. Specification Checks

We check that our model is specified correctly, e.g. whether or not the assumptions that disturbances ε_{1t} , and ε_{2t} are normally distributed and serially independent with constant volatilities are valid. If these assumptions are correct then we expect the standardized prediction errors [1] to be white noise. Note that in a multivariate case the square root of the inverse matrix F_t is obtained using Cholesky decomposition of the inverse matrix F_t into lower and upper triangular matrices. Therefore, we can represent $F_t^{-} = B_t^T x B_t$, where B_t is an upper triangular matrix. The standardized prediction errors are obtained using

$$e_t = B_t \nu_t \, , \; t = 1,...,n$$

where ν_t are prediction errors from the Kalman filter. In our case standardized prediction errors is a vector of two components derived from $\nu_{1t} = \ln m_t - E[m_t \mid I_{t-1}]$ and $\nu_{2t} = i_t - E[i_t \mid I_{t-1}]$.

As we discussed in Appendix A, we check normality, homoscedasticity and the absence of serial correlations for the standardized one-step forecast errors e_t for the test and control samples. We start with checking normality assumption by examining quantile plots and histograms of each component of the standardized prediction error vector. Figures 7, 11 and 15 display plots of the scaled prediction errors for the test and control samples respectively. The data illustrate that the means of the scaled prediction errors are zero. Figures 8, 12 and 16 show normal QQ plots of the standardized errors for the "Before", "After" and No-news sample respectively. We confirm a standard phenomenon in empirical finance of heavy-tailed distributions of the prediction errors. However, we find that the QQ plots are satisfactory and provide evidence that the normality assumptions of disturbances in the state space model are reasonable.

In order to check the no-serial correlation assumptions we construct correlogram for each component of the standard prediction errors and cross-correlogram up to the ten length. We choose a lag equal to 10 since our preliminary analysis shows that autocorrelations of order imbalances decay significantly after the ten length. Figures 9, 13 and 17 show the correlograms of the standardized prediction errors of prices and order imbalances for days after M&A announcements, before M&A news and no-news days respectively. The autocorrelations of the standardized prediction errors of order imbalances are positive but small. For example, the autocorrelation at the first lag is about 0.09 for days following merger news. The first order autocorrelations of the standardized prediction errors of order imbalances are 0.06 and 0.08 in days before M&A announcement and no-news days respectively. Order flow is a long memory process so it is not surprising to find some small autocorrelations in its scaled innovations. The autocorrelations of the scaled prediction errors of prices are statistically insignificant at the 5% level of confidence. Additionally, the cross correlograms on Figures 10, 14 and 18 do not reveal significant cross correlations between the scaled prediction errors of prices and order imbalances in the test and control samples.

We run a test for heteroscedasticity of the standardized prediction errors proposed in Section 4. We construct two exclusive subsets of the scaled prediction errors of prices for each sample, e.g. the “After”, “Before” and No-news. The F-test is applied to the ratio of the sum of squares of the prediction errors from two subsets. We repeat the same procedure for the scaled prediction errors of order imbalances. Table 13 shows the results. We can not reject the null hypothesis of homoscedasticity of innovations and error terms of the state space model at the 5% confidence level for the “Before” and no-news days and at the 10% confidence level for the days following merger news.

7.2. Robustness Checks

In order to test robustness of the estimated parameters from the state space model, we split our sample into two subsamples and estimate our model for each subsample. Specifically, we separate our sample of 53 stocks into two groups consisting of 26 and 27 stocks respectively. Tables 14-16 show the estimates of the parameter vector θ for each of the subgroups and each time period, e.g. after merger news, before merger news and in no-news days. The analysis reveals that the main results are largely unaffected. The only difference is that price impact of order imbalances in the second subsample becomes statistically indistinguishable from zero at the 5% level of confidence in the “Before” period.

Chapter 8: Conclusions and Future Research

We examined price behavior of target symbols around announcements of large US M&A deals from 2004 to 2008. All of the announcements in the sample are overnight news which is not surprising due to presumably large market impact of such news. Our findings shed the light on price discovery around M&A announcements and its contribution to accentuated intraday stock's price volatility.

First, we find evidence of a significantly more informative period in the two days following M&A announcements with the information flow per unit of time a factor 2 higher compared to the pre-announcement period and no-news days. This indicates that price discovery around M&A announcements is a protracted process that extends beyond first half hour of trading as it was found in prior work.

Second, we provide evidence of intraday (minute by minute) price adjustments around M&A announcements that contribute to better understanding of how in aggregate the market reacts to highly uncertain and significant news, and how market reaction translates into trading costs around M&A announcements. We found a significantly higher price impact in one minute intervals in the post-announcement days compared to the "Before" or no-news days. We showed that high price impact in days following M&A news is attributed to the market being more one-sided (e.g. market with significantly high absolute order imbalances over one minute intervals and high positive autocorrelation in order imbalances). Hence, one-sided order flow in days after merger news signals a greater degree of convergence in expectations of share value among agents while the market is transitioning to the new consensus value. High persistence in market sidedness implies that a one-sided market is likely to remain one-sided over one minute intervals in its transitioning to the new equilibrium price based on news.

In contrast, order flow is predominantly two-sided with a lower absolute order imbalance measure and less autocorrelated order imbalances in days without news signaling divergent opinions of the investors. This results in small and statistically insignificant price impact in no-news days. Though autocorrelation in the order flow before M&A announcements is statistically significant and positive, it is lower compared to the post-announcement period. Sarkar et al. (2008) suggest that a two-sided market is a natural state of the market.

It is likely that high autocorrelation in the order flow after M&A announcements is attributed to investor's reaction to news. Large institutional investors tend to slice and dice their orders more in the presence of information that may trigger a one–sided market with inflated trading costs. This introduces higher correlations into order flow. Also, agents with initially divergent expectations may adapt their investment strategies by observing changes in prices and placing orders in the direction of this price changes, therefore introducing additional correlations into order flow. Though this research does not premise on distinguishing what of the two factors contributes more to highly autocorrelated order flow around M&A announcements, divergent expectations environment with adaptive valuations is likely to provide a more flexible framework.

In addition, we examine patterns of the spread, volume and volatility in days surrounding merger news. We observed significantly higher volatility and volume in one minute intervals in the post-announcement period contrasted to the pre-announcement period and in days without news. These results confirm findings of prior work on in volume and volatility surges around news events.

In contrast to many prior studies that focus on increased adverse selection component of the spread after news announcements (e.g. Krinsky and Lee (1996)), we found that the spread is the lowest in days after takeover news. A market sidedness is an indication of extent of disagreement among market participants, e.g. more one-sided market signals convergence in beliefs among investors. In turn, convergence in beliefs, implies competition among trades that results in the decreased spread in days following M&A news.

Moreover, the literature that premises on divergent expectations among investors, for example, Handa et al. (HST 2003) shows that the spread is a function of the difference in valuation among agents. The spread widens with increasing divergence in opinions of investors about the underlying stock's price and narrows when the difference in valuation decreases.

The empirical results also revealed a significantly higher autocorrelation in trading activity, volume and the spread in days following M&A announcements contrasted to the "Before" and no-news sample. The large price impact in days following M&A news stems from a combination of significantly increased and autocorrelated volume with a dominating one-sided order imbalances.

On average, we did not find significant market over or under reaction to news over one minute intervals in the test and control samples. One the one hand, autocorrelated order flow creates protracted price pressure and positive autocorrelations in price changes in one minute intervals that may signal market under reaction to news. On the other hand, according to recent work in behavioral finance, investors have a whole chain of intraday reactions to news starting from under reaction that gradually develops into overreaction to news. We believe that our finding of no significant market reaction to news in one minute intervals may be a result of averaging across intervals with significant market over and under reaction to M&A news.

High positive autocorrelations across such characteristics as order imbalances, trading activity, volume, volatility and spread after M&A news are the manifestation of non-instantaneous price discovery. When actual prices fail to catch up with the continuously evolving efficient price, trades are executed at an appropriate price and transaction prices signal misleading information to investment community. Thus, non-instantaneous price discovery contributes to the pricing error. In turn, higher pricing error translates into accentuated price volatility and implies higher transaction costs and lower market's efficiency of price discovery.

Since trading is a zero-sum game, for some market participants accentuated volatility may be a source of their profit whereas for others it is a source of their loss. However, in aggregate, accentuated price volatility is costly to the market. This makes trading more difficult due to higher price uncertainty in a short period of time. Elevated price uncertainty discourages trades and contributes to higher uncertainty of portfolio returns.

Our dissertation assesses minute by minute pricing errors around M&A announcements and contributes to better understanding of trading costs. Our analysis reveals that, on average, the dispersion of pricing errors following merger news is a significant factor 5 higher compared to the "Before" period. To compare, the standard deviation of pricing errors in the "After" sample is 2% vs. 0.4% of the mid-quote price in the "Before" sample. The standard deviation of the pricing errors in the no-news days is small and statistically insignificant at the 5 % level of confidence. While we find increased implicit trading costs in the post-announcement period due to non-instantaneous price discovery, explicit trading costs that are measured by the proportional spread show a significant reduction after M&A announcements.

To compare, the proportional spread in days following M&A announcements comprises on average 0.045 % of the stock's mid-quote price, whereas the dispersion of the pricing error constitutes 2% of mid-quote price. Prior work discusses trading costs around M&A announcements solely in the context of the spread. Our findings provide evidence that the spread around M&As is a misleading measurement of trading costs since it reflects only explicit transaction costs and does not account for the implicit component of trading costs. Moreover, price discovery contributes to the inflated pricing following M&A announcements and results in significantly higher implicit trading costs compared to the spread. Our result is consistent with PSW's (2010) formulation which suggests that that price discovery is a major factor that contributes to volatility surges.

Our findings of the increased price impact, trading volume and decreased bid-ask spread for the days following merger news confirm results obtained by recent studies, for example Obizhaeva (2008). Specifically, the author examines the association of trading volume, the price impact and effective spread for traditional and crossing networks from 2001 to 2005; and she detects a positive association between the price impact and trading volume and a negative association between the spread and trading volume. The former seems to be counterintuitive and not very well explained in the market microstructure literature. Obizhaeva discusses possible factors leading to the positive price impact-volume association albeit without specific empirical evidence of a price formation process around news events.

In contrast, our study sheds more light on the relation between trading volume and price impact by presenting empirical evidence of a price discovery process.

Specifically, a stock's price does not adjust instantaneously following new information due to market friction. It is a complex dynamical process, where market participants with divergent expectations and adaptive valuations over time reveal and update their valuation of a stock's fair value as they observe the assessment of other traders and market conditions. Our empirical results show that the positive association between the price impact and trading volume is consistent with price discovery around news events that triggers more one-sided trading.

On the one hand, significant price changes in one minute intervals following merger news become price trends due to high autocorrelation in order flow. Protracted price runs are the manifestation of imperfect non instantaneous price discovery which adds to the pricing error. The pricing error, in turn, translates into heightened stock price volatility and represents implicit trading costs. On the other hand, with continuous trading, these price runs are an essential part of a price discovery process that eventually leads to adjustment of prices to new information.

In the summary, this research contributes to the existing literature by providing empirical evidence on price behavior around M&A news. Specifically, we find that price discovery following M&A news events manifests itself in protracted order flow generated price pressure. Our results shed light on counterintuitive findings of the positive relation between trading volume and market impact documented in the recent market microstructure literature. We show that price impact in one minute intervals is the effect of imperfect non-instantaneous price discovery that contributes to the pricing error and inflates implicit trading costs. Our findings suggest a primary role of price discovery in trading costs following M&A announcements.

As a topic for the future research, we suggest extending our analysis to examining a price discovery process around other significant market wide and firm specific information events. Another possible direction of the research would be estimation and comparison of price discovery effects for the different intraday periods. Specifically, the first minutes following market openings is a particularly interesting period when the market experiences significant stress, and price discovery effects are expected to be magnified.

Another interesting direction of the future research is to examine in more detail how market reaction to M&A evolves over time. Specifically, it will be interesting to separate intraday time periods with significant market under and over reaction to merger news. It is also worth examining price behavior beyond a two-day horizon to reveal how much time it takes the market to fully digests M&A news. This research venue is a complicated process that presumably will require filtering public news feeds to be able to address the long run price dynamics that are solely attributed to M&A information.

APPENDIX A

A State Space Methodology

1. Linear Gauss-Markov State Space Model

State space time series analysis began with the seminal paper of Kalman (1960) and emerged from the field of engineering. The technique of state space analysis is based on the Kalman filter. The Kalman filter gives a linear, unbiased, and minimum error variance recursive algorithm to optimally estimate the unknown state of a dynamical system from noisy data taken at discrete real-time intervals. It has been widely used in many areas of industrial and research applications such as video and laser estimations and satellite navigation.

The Kalman filter has also become useful for applications to various problems in economics and finance. A major advantage of the Kalman filter is a robust and efficient signal extraction from noise corrupted observations with missing values. However, in spite of its importance and advantages, the Kalman filter technique is underrepresented in market microstructure studies.

The state space framework views observed variables as representing noisy information about real, though unobservable, state variables that form a state vector. A-priori information about the dynamics of the state vector is used to formulate a stochastic model equation. The stochastic model equation describes the dynamic evolution of the unobservable state vector and contains innovation terms that drive the model dynamics. The actual observations supply noisy information about the state variables. An observation equation links the observed variables to the state vector and contains unobservable disturbances. These disturbances represent deviations of actual observed signals from the states and are referred to as noise.

Thus, the state space form is based on two important sets of system equations: the model equations which describes the dynamic evolution of the unobservable state variables; the second set of equations relates the state variables to the variables which can only be observed with measurement noise. The standard linear first-order Gauss-Markov state space representation is given by model equation and observation equation.

A model equation:

$$y_{t+1} = A_t(\theta) y_t + Q_t(\theta)\varepsilon_{1t}$$

where y_t is an unobservable state vector and ε_{1t} is a Gaussian noise term such that

$E[\varepsilon_{1t}] = 0$ and $E[\varepsilon_{1t}\varepsilon'_{1s}] = T_t(\theta)$ for $s = t$ and 0 otherwise.

Initial state is normally distributed and uncorrelated with the error term:

$y_0 \sim N(y_0, P_0)$ and $E[y_0\varepsilon'_{1t}] = 0, \forall t$, where P_0 is a variance-covariance matrix.

The system matrices A_t, Q_t and T_t depend on a parameter vector θ.

An observation equation:

$$z_t = H_t(\theta) y_t + \varepsilon_{2t}$$

where z_t is a vector of observations and ε_{2t} is a Gaussian noise term such that

$E[\varepsilon_{2t}] = 0$ and $E[\varepsilon_{2t}\varepsilon'_{2s}] = R_t(\theta)$ for $s = t$ and 0 otherwise, and

$E[\varepsilon_{1t}\varepsilon'_{2s}] = 0, \forall t, s$ and $E[y_0\varepsilon'_{2t}] = 0, \forall t$.

The system matrices H_t and R_t depend on the parameter vector θ.

If some of the elements of thee state vector y_t follow nonstationary process, the initial state vector y_0 cannot be specified properly and is regarded as being partially diffuse (Durbin and Koopman (2001)).

The estimation procedure for the state space form therefore has two aspects: measuring the unobservable state including prediction, filtering and smoothing; and estimation of an unknown vector of parameters. We start first with the first aspect by providing a description of the Kalman filter.

2. The Kalman Filter

As noted, instead of being able to observe the state vector y_t directly, we can only observe some noisy function z_t of y_t. The problem of determining the state of the system from noisy measurement z_t is called estimation. In general, the estimation problem can be classified upon the available and processed information into three different problems according to the following definition. Considering the problem of estimating the state vector using the information up to time s, denoted by the information set $\mathrm{I}_s = \{z_s, ..., z_2, z_1\}$, we differentiate between three cases

- filtering problem : for $t = s$,
- smoothing problem: for $t < s$, and
- prediction problem: for $t > s$.

The central part of the filtering problem is the Kalman filter which is the optimal linear unbiased recursive estimator. The optimality is understood in the sense of a minimum mean square estimator (MMSE). The Kalman filter presents a set of equations which allows an estimate to be updated once a new observation becomes available. The filtering process is carried out in two distinct parts: prediction and updating. The prediction step consists of forming an optimal predictor of the next observation, given all the information available up to time *t*. The Kalman filter extrapolates the mean and variance of the state vector utilizing the information set I_{t-1} and calculates a so-called a priori estimate for time $t-1$. The a priori state estimate is updated with the new information arriving at time $t-1$. The result of this step is the filtered estimate or the a posteriori estimate.

In the prediction step, the conditional expectation of the state vector mean and variance are calculated given the information set I_{t-1} up to time $t-1$:

$$y_t|_{t-1} = E[y_t \mid I_{t-1}] = A_t y_{t-1}$$

$$P_t|_{t-1} = E[(y_t - E[y_t \mid I_{t-1})(y_t - E[y_t \mid I_{t-1})'] = A_t P_{t-1} A_t' + Q_t T_t Q_t'$$

The prediction error denoted by v_t is given by

$$v_t = z_t - z_t|_{t-1} = z_t - H_t y_t$$

The variance-covariance matrix of v_t is defined as

$$F_t = H_t P_t H_t' + R_t$$

In the updating step, the Kalman filter provides the inference on $y_t|_{t-1}$ by including the newly available information at time t such that the variance –covariance matrix F_t of the prediction error v_t is minimal. This finally results in the filtered estimate of the state vector mean and variance:

$$y_t|_t = E[y_t \mid I_t] = A_t y_{t-1} + K_t v_t$$

$$P_t|_t = E[(y_t - E[y_t \mid I_t)(y_t - E[y_t \mid I_t)'] = P_t|_{t-1} - K_t H_t P_t|_{t-1}$$

where $K_t = P_t|_{t-1} H_t' F_t^{-}|_{t-1}$ is the Kalman gain matrix.

3. Initialization

The sequence of filtering equations is applied recursively as each new observation becomes available. The recursion algorithm starts with a feasible choice of the parameter vector θ and corresponding state vector y_0 and variance-covariance matrix P_0. Note that as we discussed above, the distribution of the initial vector is normal with known y_0 and P_0. However, the usual situation in practice is when nothing is known about the distribution of y_t. In this situation it is reasonable to represent y_t as having a diffuse prior density, that is, fix y_0 at an arbitrary value and let $P_0 \to \infty$. This process is called diffuse initialization of the Kalman filter and the resulting filter is called the diffuse Kalman filter.

4. Parameter Estimation

The parameter vector θ is estimated using the likelihood function of the state space model. The likelihood function is given by the joint density of the observational data:

$$LogL(z_t, \theta) = \sum_{t=1}^{n} \log p(z_t(\theta) \mid I_{t-1})$$

In the state space model, $p(z_t(\theta) \mid I_{t-1})$ is a Gaussian density with mean $E[y_t \mid I_{t-1}]$ and variance F_t:

$$LogL(z_t, \theta) = -\frac{n}{2}\log 2\pi - \frac{1}{2}\sum_{t=1}^{n}(\log F_t + F_t^{-1} v_t^{\,2})$$

where v_t is the prediction error and F_t is its variance.

In order to estimate the unknown parameters from the log-likelihood function we need to choose an appropriate optimization algorithm to minimize - $L(z_t, \theta)$ with respect to θ:

$$\theta' = \arg\min_{\theta} \log L(\ z_t, \theta)$$

The necessary and sufficient conditions for a local minimum θ' are defined by the conditions for the gradient and its first derivative:

$$\nabla L(z_t, \theta') = 0$$

$\nabla^2 L(z_t, \theta') > 0$

In order to estimate the model parameters, the usual procedure of a quasi-Newton method is used. Parameter identification is a serious problem. Identification is a link between the mathematical model world and the real world of data. A model is said to be not identifiable, if there are observationally equivalent structures of model parameters θ that imply the same distribution for the observable random outcomes z_t, i.e. there exist different parameter vectors that lead to the same likelihood $LogL(z_t, \theta)$. Dealing with an unidentifiable parameter vector θ is a severe problem since alternative parameter structure usually lead to different causal interpretation s in the context of the investigated model. Thus, the uniqueness of the likelihood must be guaranteed for all possible parameter vectors , because the true parameter structure is not known.

5. Diagnostic checking

The assumptions that the disturbances ε_{1t} and ε_{2t} are normally distributed and serially independent with constant variances imply normality, homoscedasticity and the absence of serial correlations for the standardized one-step forecast errors

$e_t = \frac{v_t}{\sqrt{F_t}}$ $t = 1,...,n$ or $t = 2,...,n$ in the diffuse case [1]

Durbin et al [2001] show that normality assumptions are valid if the third and the forth moments of distribution , i.e. skewness S and kurtosis K are asymptotically normally distributed as:

$S \sim N(0, \frac{n}{6})$ and $K \sim N(3, \frac{24}{n})$

The authors also suggest a simple test for heteroscedasticity by comparing the sum of squares of two exclusive subsets of the sample

$$H(h) = \frac{\sum_{t=n-h+1}^{n} e_t^2}{\sum_{t=1}^{h} e_t^2} \sim F_{h,h} \qquad [2]$$

where the denominator starts at $t = 2$ in the diffuse case. Under he null hypothesis of homoscedasticity, the ratio of the sum of squares is $F_{h,h}$ - distributed. Serial autocorrelations are expected to be checked with the correlogram of the forecast errors. If the specification is correct, the correlogram should reveal insignificant serial correlation. Additionally, a standard pormanteau test for serial correlation should be applied to the standardized one-step forecast errors e_t .

APPENDIX B.

ALBERTSON'S LLC
ARCHSTONE-SMITH TRUST
AMSOUTH BANCORPORATION
ALLTEL CORP
ALLIED WASTE INDUSTRIES
AWE
BAC NOTRH AMERICA
BCE INC
BELLSOUTH CORP
BURLINGRTON RESOURCES INC
CHARTER ONE FIN
CINERGY CORP
CAREMARK RX INC
GENETECH INC
ELECTRONIC DATA SYSTEMS
EQUITY OFFICE PROPERTIES
FLEETBOSTON FINANCIAL Co
FIRST DATA CORP
FISHER SCIENTIFIC INTL INC
GILLETTE COMPANY
GUIDANT CORP
GOLDEN WEST FINANCIAL CORP
GEORGIA-PACIFIC LLC
GLOBALSANTAFE CORP
HCA INC
HARRAH'S ENTERTAINMENT
HILTON HOTELS CORP
KRAFT FOODS INC-CLASS A
KERR-MCGEE CORP
KNIGHT INC
KRB
KEYSPAN CORP
LYONDELL CHEMICAL COMPANY
MAY DEPARTMENT STORES
MELLON FINANCIAL CORP
NORTH FORK BANCORPORATION
NORTHROP GRUMMAN SPAC
BANK ONE CORP
PHELPS DODGE CORP
PHARMACIA CORP
ROUSE CO/THE
RIO TINTO PLC
SUNGARD DATA SYSTEMS
AT&T CORP
TRIBUNE CO
TRANE INC

TIME WARNER CABLE
ENERGY FUTURE HOLDINGS CORP
UNOCAL CORP
UST INC
UNIVISION COMMUNICATIONS-A
VIACOM INC-CLASS B
WRIGLEY WM JR CO

Table 1. Market and Stock-Specific Price Changes Around M&A Announcements

The table shows the means and standard errors of the close to open returns for target stocks and market (SPY). Close price from the second day of and open price of the first day of each sample are used to construct returns. The returns are expressed in basis points. We report the statistics for two groups of target stocks: those with price up trend and those with price down trend after M&A news. Bold entries indicate statistically significant difference in at the 5% confidence level in means between the target stocks and market.

Target stocks with price up trend after M&A announcements.
Number of target stocks is 36.

	Before	**After**	**No-news**
Target Stocks	**198** (40)	**366 (80)**	-37 (18)
Market (SPY)	4 (32)	5 (30)	-6 (10)

Target stocks with price down trend after M&A announcements.
Number of target stocks is 17

	Before	**After**	**No-news**
Target Stocks	**208** (29)	**-188 (30)**	28 (16)
Market (SPY)	28 (15)	0 (20)	10 (6)

Table 2. Descriptive Statistics

The table shows the means and medians of volume, volatility, liquidity, the number of trades, the absolute difference in the number of buy-triggered and sell-triggered orders (shares) and the absolute order imbalance metric. The trading day from 10 A.M. to 3:30 P.M. is divided into one minute intervals. The variable VOLUME is number of total shares traded in the interval; HILO is ratio of the highest to the lowest price in the interval minus one expressed as a percent; NUM is total number of trades in the interval; SPREAD is the proportional spread ratio of the difference between ask and bid prices to the quote mid-point over a one minute interval presented in basis points. The variable ABS_DIFF_NUM is the absolute difference between number of buyer initiated and seller initiated trades. The variable ABS_DIFF_SHARES is the absolute difference between number of buyer initiated and seller initiated shares. A ratio of ABS_DIFF_NUM to NUM is the absolute order imbalance, AOIM, multiplied by 100. The "Before" sample consists of the two days before M&A announcements. The "After" sample consists of the day of the M&A news release and the following day. The "No-News" sample is constructed from no-news days preceding M&A events after excluding days with Core CPI, PPI, Employees on Non-Farm Payroll, Quarterly Earnings Reports and days with high absolute close-to-close returns vs. market. Excess returns are calculated relative the S& P500. Days with top 30% absolute relative returns vs. market are excluded to mitigate potential new effects in the control sample. The three samples are constructed for 53 target NYSE stocks that have been reported in major US corporate restructuring news from January 02, 2004 to

December 31, 2008. Bold entries indicate statistically significant difference at the 5% confidence level in means or medians between the test samples and the control sample.

	Before		After		No-news	
	Mean	Median	Mean	Median	Mean	Median
VOLUME	**9,141**	**4,562**	**31,016**	**23,272**	5,188	3,163
NUM	**10.61**	**8.61**	**16.32**	**12.52**	8.43	7.06
SPREAD	5.48	4.22	**4.55**	**3.60**	5.38	4.45
HILO	0.06	0.06	**0.08**	**0.07**	0.05	0.04
ABS_DIFF_NUM	**4.40**	**3.70**	**6.32**	**5.22**	3.65	3.47
ABS_DIFF_SHARES	**5,999**	**2,635**	**19,643**	**13,348**	3,136	1,939
AOIM	52.35	50.79	45.78	44.97	53.94	55.06

Table 3. Correlation Structure

The table shows the means and medians of one lag autocorrelations for volume, volatility, liquidity, number of trades and the absolute difference in the number of buy-triggered and sell-triggered orders (shares). The trading day from 10 A.M. to 3:30 P.M. is divided into one minute intervals. Bold entries indicate significantly different difference at the 5% confidence level in means or medians between the test samples and the control sample.

	Autocorrelations Before		Autocorrelations After		Autocorrelations No-news	
	Mean	Median	Mean	Median	Mean	Median
VOLUME	0.22	0.19	**0.31**	**0.32**	0.20	0.19
NUM	**0.33**	0.30	**0.40**	**0.38**	0.28	0.28
SPREAD	0.33	0.32	**0.39**	**0.41**	0.31	0.32
HILO	**0.29**	0.26	**0.35**	**0.35**	0.23	0.21
OIM	0.18	0.17	**0.22**	**0.21**	0.17	0.15

Table 4. The Augmented Dickey-Fuller Test for Order Imbalance Measures (OIM)

The table shows Dicker-Fuller t-statistics for order imbalance measures for each test sample. The null hypothesis is that OIM is characterized by a random walk vs. alternative that OIM is stationary process. The table reports 1% and 5% critical t-values.

	Before	After	No-news
T-statistics	-148.34	-144.85	-150.90
1% Critical Value	-2.58	-2.58	-2.58
5% Critical Value	-1.95	-1.95	-1.95

Table 5. First Order Autoregression Models for Order Imbalance Measures (OIM)

The table shows the mean, standard error and t-statistics of the autocorrelation coefficients for OIM for each test sample.

The "Before" sample, s = 1.
R-square = 4%

Parameter	Mean	Std. Error	T-stat
ρ_1	0.187	0.005	34.21

The "After" sample, s = 2.
R-square = 5%

Parameter	Mean	Std. Error	T-stat
ρ_2	0.219	0.005	40.71

The "Control" sample, s = 3.
R-square = 3%

Parameter	Mean	Std. Error	T-stat
ρ_3	0.186	0.005	34.70

Table 6. Volatility of Price and Order Imbalances

The table reports the volatility of log returns based on one minute mid-quotes m_t and volatility of error term ξ_t in autoregression for OIM for the Before, After and Control samples.

Parameter	Before Std. Deviation	After Std. Deviation	No-news Std. Deviation
$\ln(\frac{m_t}{m_{t-1}})$	0.037	0.030	0.029
ξ_t	0.619	0.543	0.026

Table 7. The Estimates of Parameters for the "Before" Sample

This table displays estimates of the parameter vector θ for the days before M&A news. The table reports the mean, standard errors and 95% confidence level intervals. Bold entries indicate statistically significant parameters at the 5% confidence level.

Parameter	Mean	Std. Error	95% CI
φ	**0.9292**	0.0102	0.9090 0.9494
α	-0.0003	0.0107	-0.0215 0.0209
β	**0.0162**	0.0051	0.0042 0.02832
σ_{e1}	**0.0277**	0.00424	0.0193 0.0361
σ_{e2}	**0.0884**	0.0113	0.0660 0.1108
$\sigma_{\eta 1}$	**0.0007**	0.0001	0.0005 0.0096
$\sigma_{\eta 2}$	**0.5878**	0.0668	0.4555 0.7201

Table 8. The Estimates of Parameters for the "After" Sample

This table displays estimates of the parameter vector θ for the days after M&A news. The table reports the mean, standard errors and 95% confidence level intervals. Bold entries indicate statistically significant parameters at the 5% confidence level.

Parameter	Mean	Std. Error	95% CI
φ	**0.9608**	0.0030	0.9548 0.9667
α	-0.0007	0.0272	-0.0545 0.0532
β	**0.0978**	0.0064	0.0851 0.1105
σ_{e1}	**0.0437**	0.0091	0.0257 0.0617
σ_{e2}	**0.0522**	0.0118	0.0288 0.0756
$\sigma_{\eta 1}$	**0.0013**	0.0005	0.0003 0.0022
$\sigma_{\eta 2}$	**0.5237**	0.1099	0.3061 0.7413

Table 9. The Estimates of Parameters for "No-News" Sample

This table displays estimates of the parameter vector θ for no-news days. The table reports the mean, standard errors and 95% confidence level intervals. Bold entries indicate statistically significant parameters at the 5% confidence level.

Parameter	Mean	Std. Error	95% CI
φ	**0.9363**	0.0107	0.9151 0.9575
α	-0.0002	0.0105	-0.0209 0.0206
β	0.0019	0.0055	-0.0089 0.0129
σ_{e1}	**0.0224**	0.0071	0.0083 0.0365
σ_{e2}	**0.0795**	0.0161	0.0476 0.1114
$\sigma_{\eta 1}$	**0.0008**	0.0003	0.0002 0.0014
$\sigma_{\eta 2}$	**0.6003**	0.1322	0.3385 0.8621

Table 10. The Augmented Dickey-Fuller Test for the Estimated Order Imbalance Measures (OIM)

The table shows Dicker-Fuller t-statistics for the estimated order imbalance measures for each test sample. The null hypothesis is that OIM is characterized by a random walk vs. alternative that OIM is stationary process. The table reports 1% and 5% critical t – values.

	Before	After	No-news
T-statistics	-21.223	-19.823	-30.475
1% Critical Value	-2.58	-2.58	-2.58
5% Critical Value	-1.95	-1.95	-1.95

Table 11. The Absolute Order Imbalances around M&A News

The table shows the means and medians of the absolute order imbalance metric, OIM multiplied by 100. Bold entries indicate statistically significant difference at the 5% confidence level in means or medians between the test samples and the control sample.

	Before		After		No-news	
	Mean	Median	Mean	Median	Mean	Median
AOIM	**12.03**	**10.01**	**14.11**	**11.21**	10.07	8.91

Table 12. The Estimates of the Pricing Error

This table reports the estimates of the standard deviation of the pricing error expressed in percent of the stock price for the "After", "Before" and "No-news" samples. The standard errors of the estimated pricing errors are reported in brackets. Bold entries indicate statistically significant parameters at the 5% confidence level.

	Before	**After**	**No-news**
Parameter	Standard Deviation	Standard Deviation	Standard Deviation
δ	**0.4%** (0.1)	**2%** (0.4)	0.1% (0.07)

Table 13. Heteroscedascticity Test

This table reports observed values of F statistics obtained from heteroscedasticity test using the standardized prediction errors of price e_{1t} and order imbalances e_{2t}. The null hypothesis is homoscedasticity of the innovations and error terms in the state space model. Entries with * and (**) indicate statistically significant parameters at the 5% and 10% confidence level.

Variable	**Before F-statistics**	**After F-statistics**	**No-news F-statistics**
e_{1t}	0.85*	1.01**	0.84*
e_{2t}	0.98*	1.02**	0.98*

Table 14. Robustness Check for the "Before" Sample

This table displays estimates of the parameter vector θ for the days before M&A news for two subsamples. Subsample 1 consists of the first 26 stocks from our sample and Subsample 2 has remaining 27 stocks. The table reports the mean, standard errors and 95% confidence level intervals. Bold entries indicate statistically significant parameters at the 5% confidence level.

Subsample 1

Parameter	Mean	Std. Error	95% CI
φ	**0.9522**	0.0059	0.9404 0.9640
α	-0.0003	0.0076	-0.0155 0.0149
β	**0.0407**	0.0178	0.0051 0.0763
σ_{e1}	**0.0491**	0.0179	0.0133 0.0849
σ_{e2}	**0.0521**	0.0186	0.0149 0.0893
$\sigma_{\eta 1}$	**0.0007**	0.0003	0.0001 0.0013
$\sigma_{\eta 2}$	**0.7644**	0.2802	0.2040 1.3248

Subsample 2

Parameter	Mean	Std. Error	95% CI
φ	**0.8657**	0.0235	0.8187 0.9127
α	-0.0004	0.0083	-0.017 0.0162
β	0.0149	0.0081	-0.0013 0.0311
σ_{e1}	**0.0320**	0.0013	0.0294 0.0346
σ_{e2}	**0.1220**	0.0323	0.0574 0.1866
$\sigma_{\eta 1}$	**0.0007**	0.0002	0.0011 0.0003
$\sigma_{\eta 2}$	**0.5011**	0.0495	0.40206 0.60014

Table 15. Robustness Check for the "After" Sample

This table displays estimates of the parameter vector θ for the days after M&A news for two subsamples. Subsample 1 consists of the first 26 stocks from our sample and Subsample 2 has remaining 27 stocks. The table reports the mean, standard errors and 95% confidence level intervals. Bold entries indicate statistically significant parameters at the 5% confidence level.

Subsample 1

Parameter	Mean	Std. Error	95% CI
φ	**0.9813**	0.0022	0.9769 0.9857
α	-0.0007	0.0097	-0.0201 0.0187
β	**0.1411**	0.0651	0.0109 0.2713
σ_{e1}	**0.0537**	0.0263	0.0011 0.1063
σ_{e2}	**0.0419**	0.0203	0.0012 0.0826
$\sigma_{\eta 1}$	**0.0013**	0.0007	0.0298 0.0326
$\sigma_{\eta 2}$	**0.5317**	0.2600	0.0117 1.0517

Subsample 2

Parameter	Mean	Std. Error	95% CI
φ	**0.9258**	0.0117	0.9024 0.9492
α	-0.0021	0.0086	-0.0193 0.0151
β	**0.0353**	0.0134	0.0085 0.0621
σ_{e1}	**0.0312**	0.0200	-0.0088 0.0712
σ_{e2}	**0.0812**	0.0328	0.0156 0.1468
$\sigma_{\eta 1}$	**0.0013**	0.0007	-0.0001 0.0027
$\sigma_{\eta 2}$	**0.4726**	0.2035	0.0656 0.8796

Table 16. Robustness Check for "No-News" Sample

This table displays estimates of the parameter vector θ for no-news days for two subsamples. Subsample 1 consists of the first 26 stocks from our sample and Subsample 2 has remaining 27 stocks. The table reports the mean, standard errors and 95% confidence level intervals. Bold entries indicate statistically significant parameters at the 5% confidence level.

Subsample 1

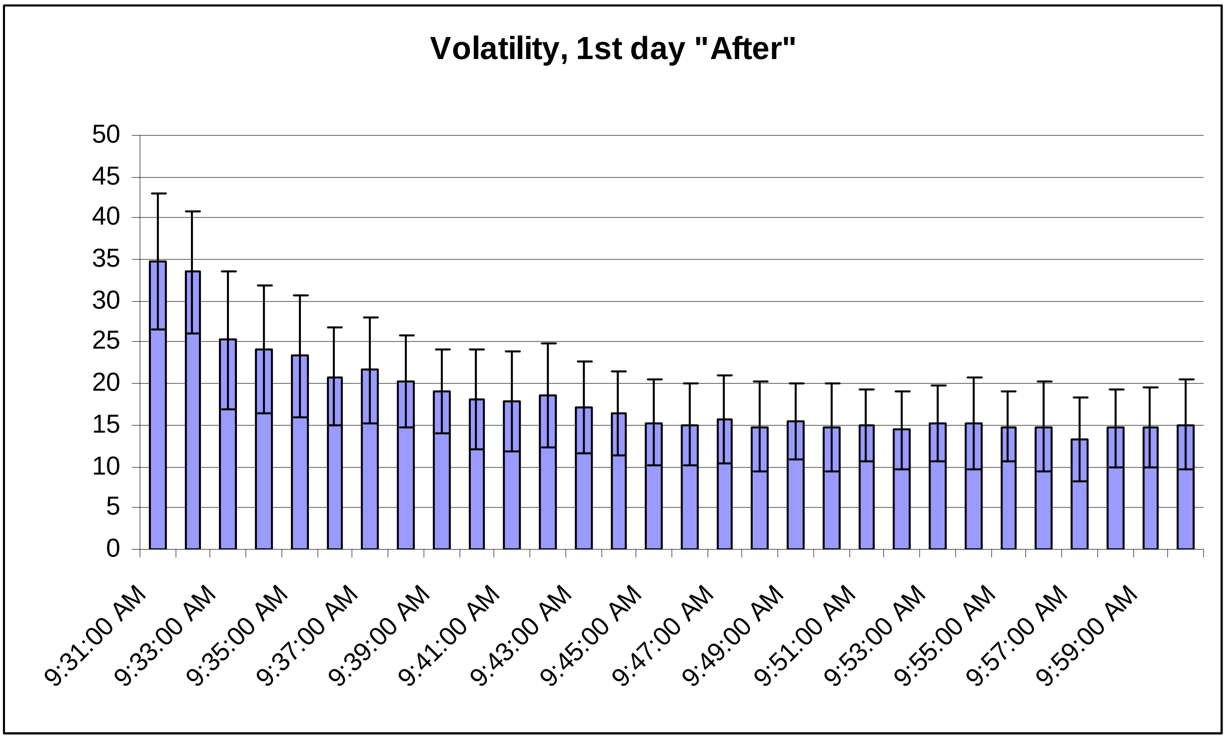
Parameter	Mean	Std. Error	95% CI
φ	**0.9406**	0.0052	0.9090 0.9494
α	-0.00003	0.0078	-0.0215 0.0209
β	0.0285	0.0339	0.0051 0.0273
σ_{e1}	**0.0396**	0.0165	0.0066 0.0726
σ_{e2}	**0.0577**	0.0245	0.0087 0.1067
$\sigma_{\eta 1}$	**0.0007**	0.0003	0.0001 0.0013
$\sigma_{\eta 2}$	**0.8558**	0.3581	0.1396 1.572

Subsample 2

Parameter	Mean	Std. Error	95% CI
φ	**0.8428**	0.0384	0.9090 0.9494
α	-0.0004	0.0078	-0.0215 0.0209
β	0.0076	0.0064	0.0051 0.0273
σ_{e1}	**0.0283**	0.0070	0.0143 0.0423
σ_{e2}	**0.1173**	0.0056	0.1061 0.1285
$\sigma_{\eta 1}$	**0.0008**	0.0003	0.0002 0.0014
$\sigma_{\eta 2}$	**0.4654**	0.1787	0.108 0.8228

Figure 1. Volatility in the First Half-Hour for the "After" Sample

This figure shows minute-by-minute volatililty (HILO) in the first half-hour for the "After" sample (for two days following M&A news). HILO is expressed in percents.



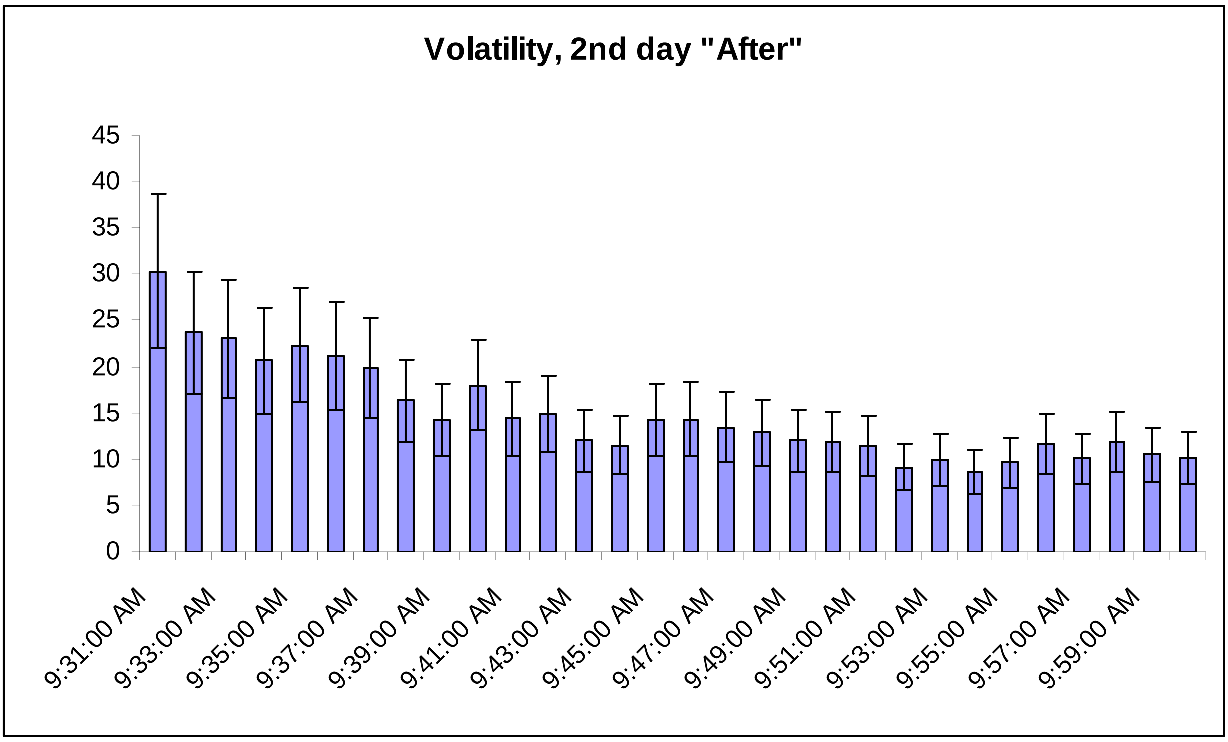
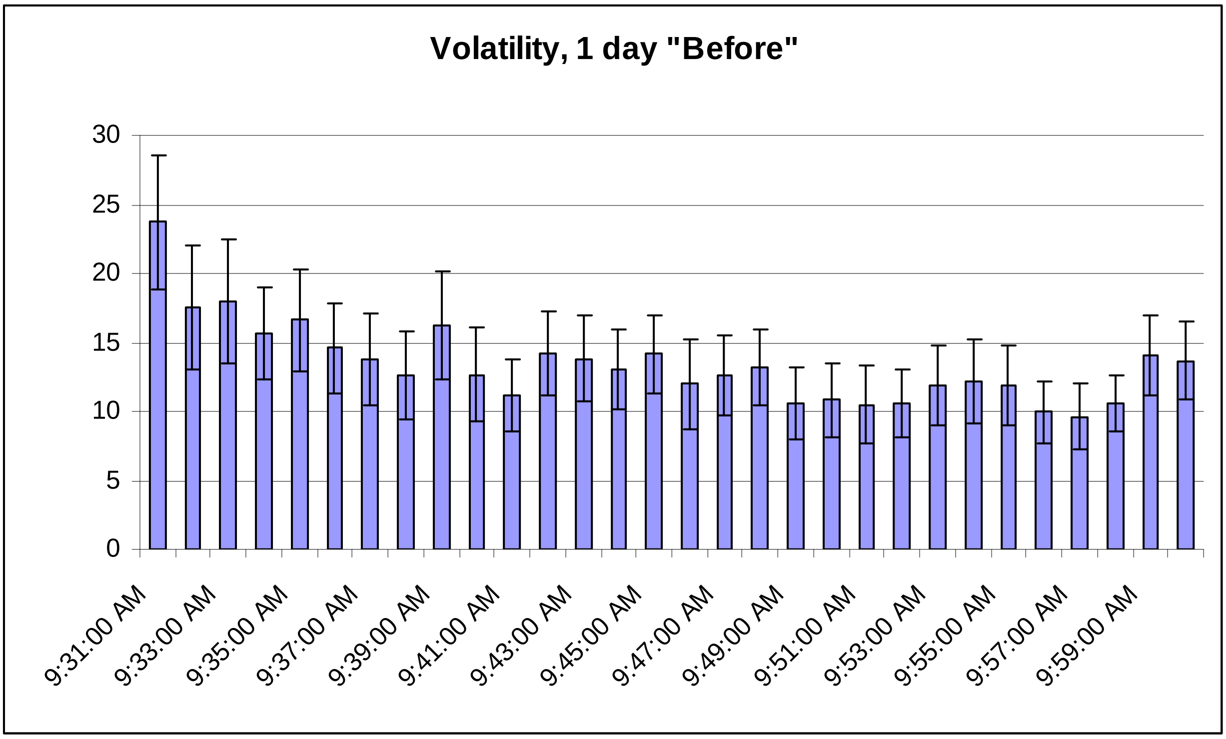


Figure 2. Volatility in the First Half-Hour for the "Before" Sample

This figure shows minute-by-minute volatililty (HILO) in the first half-hour for the "Before" sample (for two days prior to M&A news). HILO is expressed in percents.



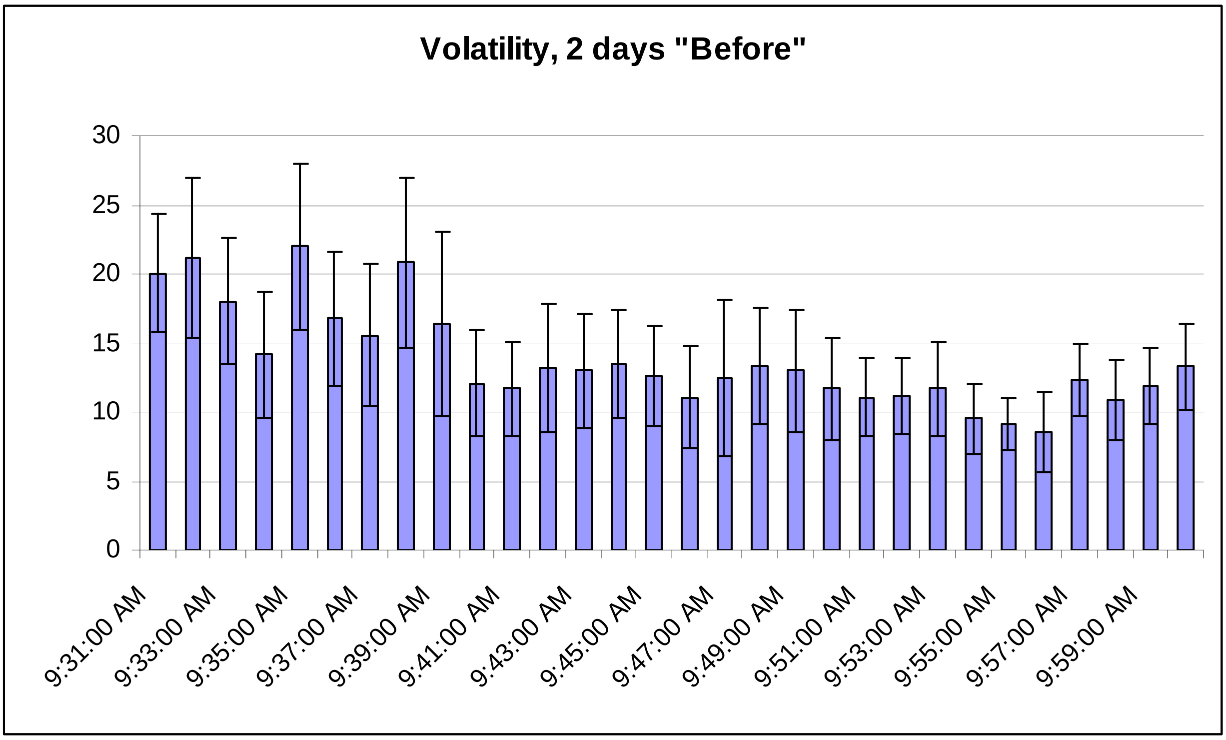
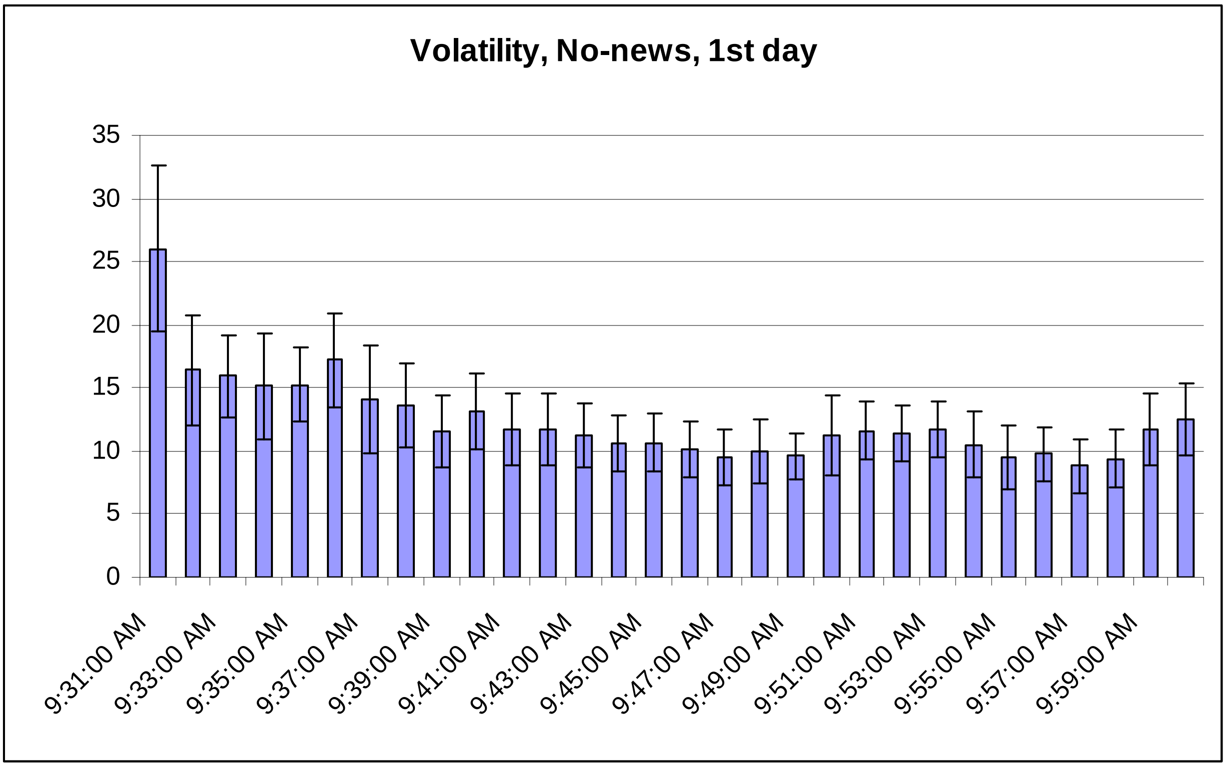


Figure 3. Volatility in the First Half-Hour for the "No-News" Sample

This figure shows minute-by-minute volatililty (HILO) in the first half-hour for the "No-news" sample. HILO is expressed in percents.



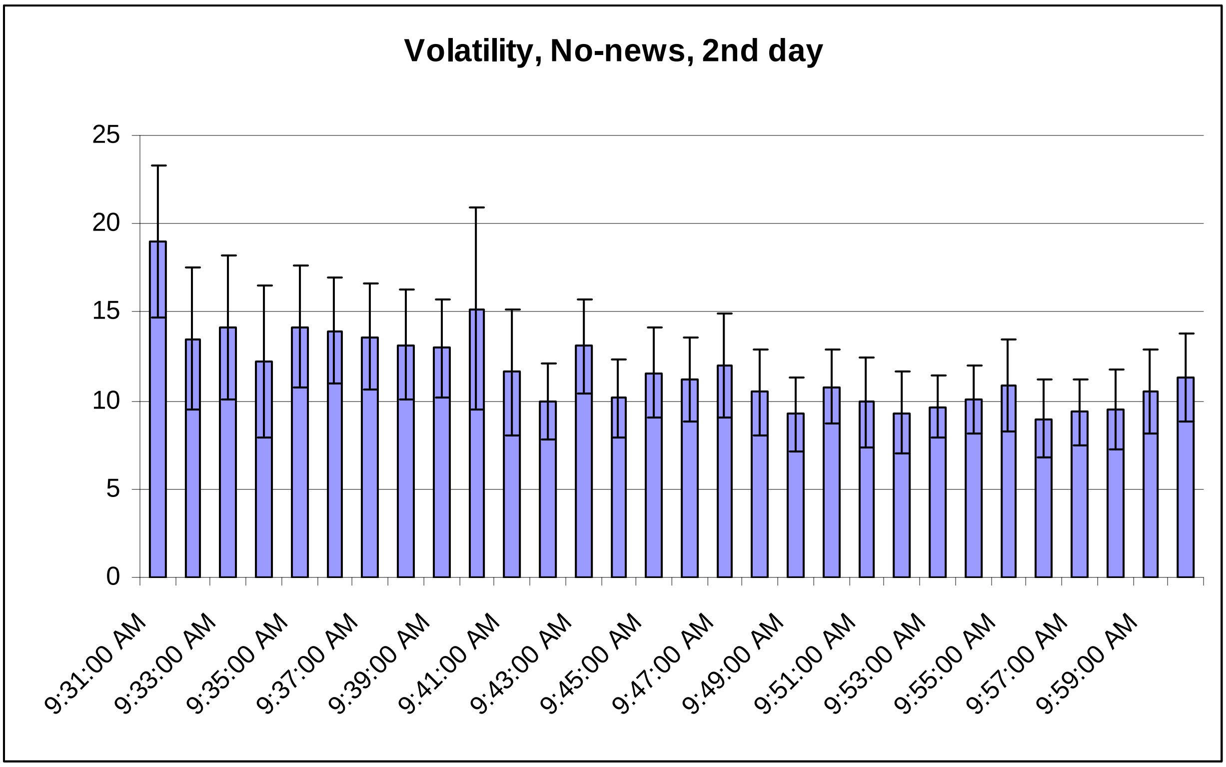
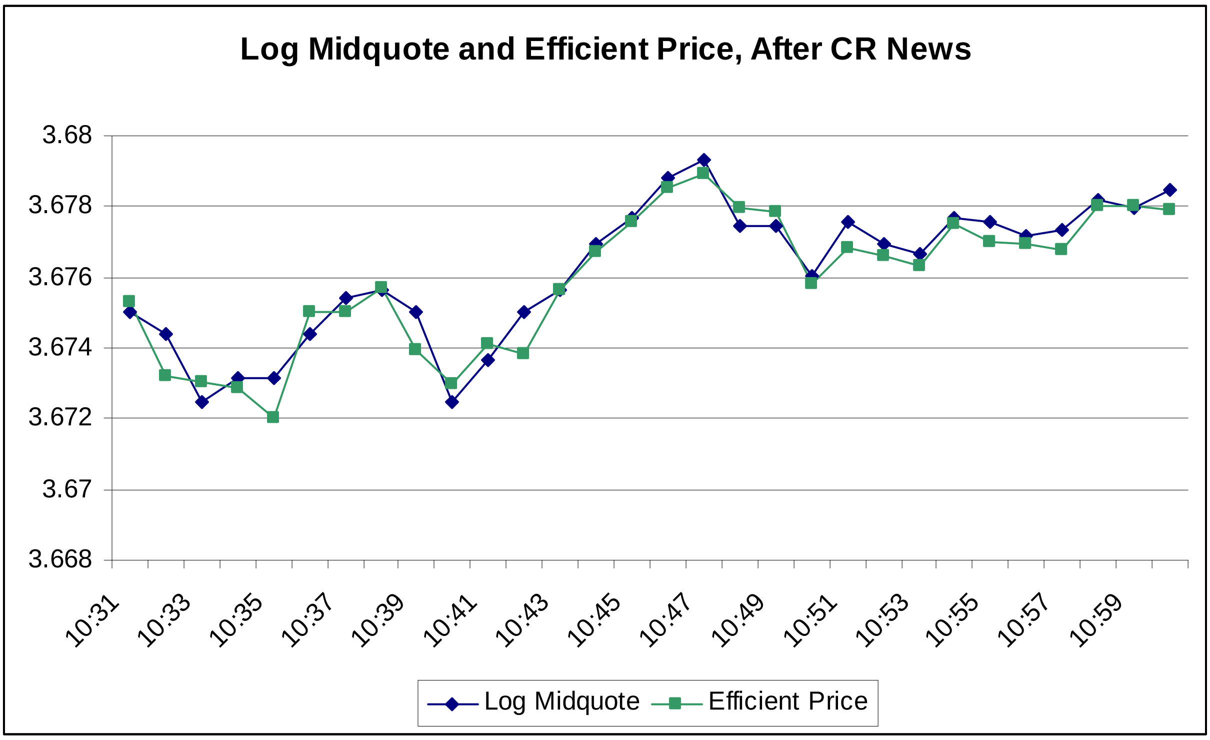


Figure 4. Observed and Estimated Price and Order Imbalances for the "After" Sample

This figure displays minute by minute log midquotes, estimated efficient price, observed order imbalances and estimated order imbalances in the day following M&A news from 10:30 A.M. to 11 A.M. for one symbol (FBF, Fleet Boston Financial). Order imbalance is the difference between the number of buy order and sell orders normalized by the total number of trades over one minute interval.



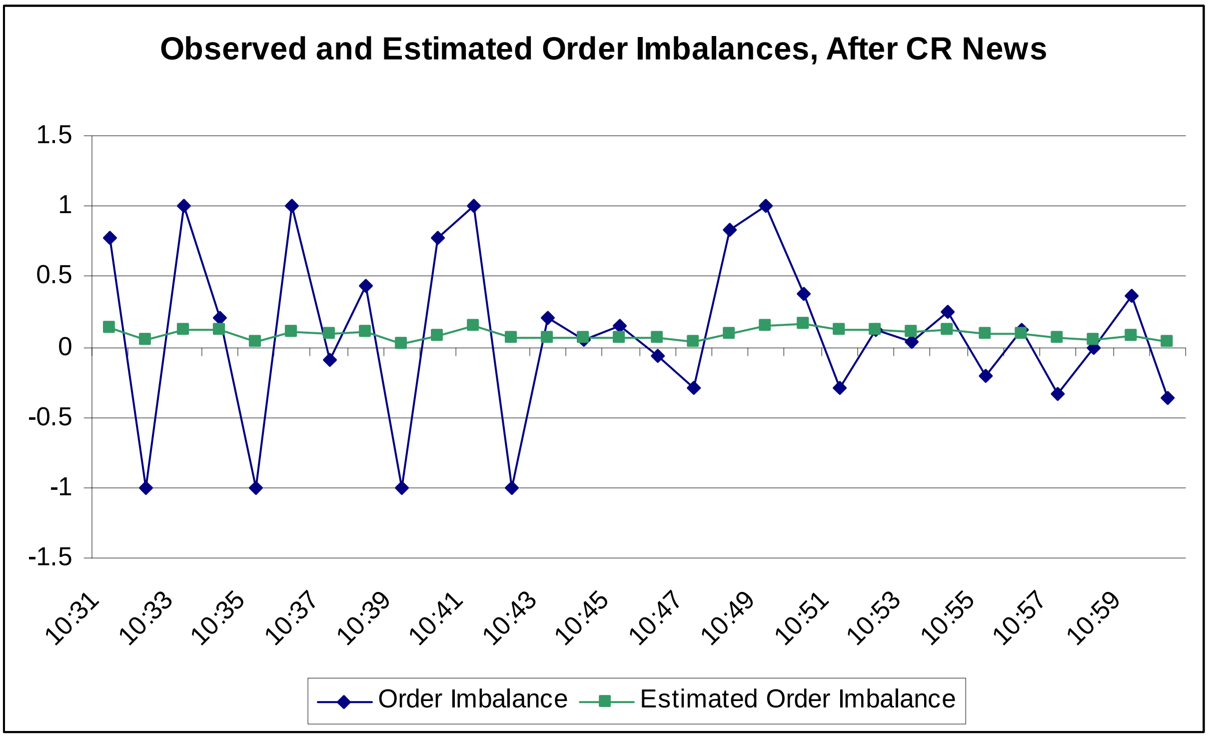
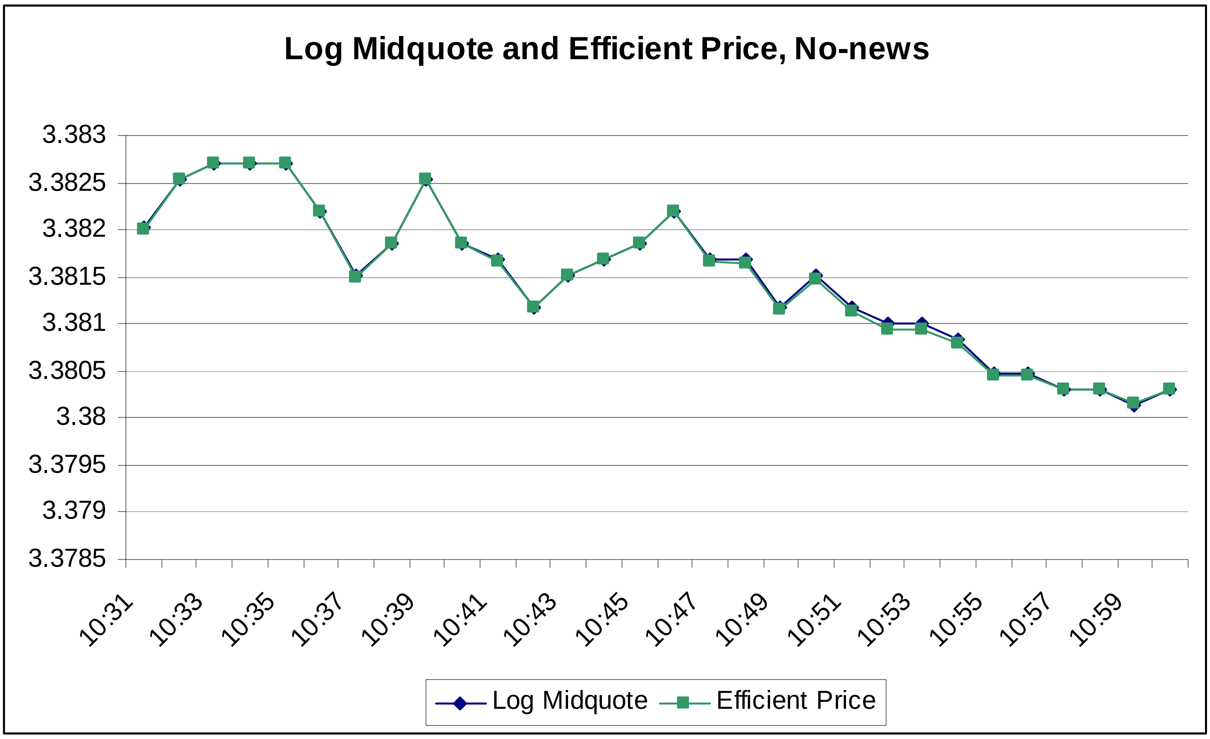


Figure 5. Observed and Estimated Price and Order Imbalances for "No-News" Sample

This figure displays minute by minute log midquotes, estimated efficient price, observed order imbalances and estimated order imbalances in no-news day from 10:30 A.M. to 11 A.M. for one symbol (FBF, Fleet Boston Financial). Order imbalance is the difference between the number of buy order and sell orders normalized by the total number of trades over one minute interval.



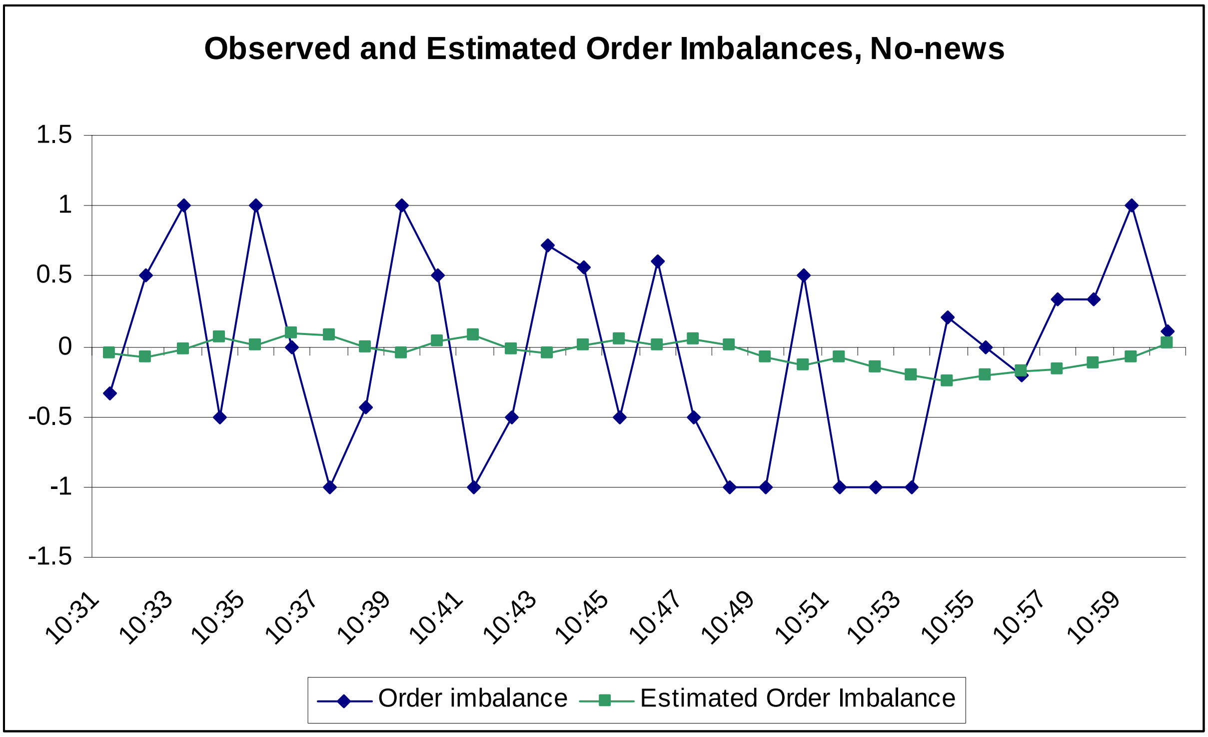
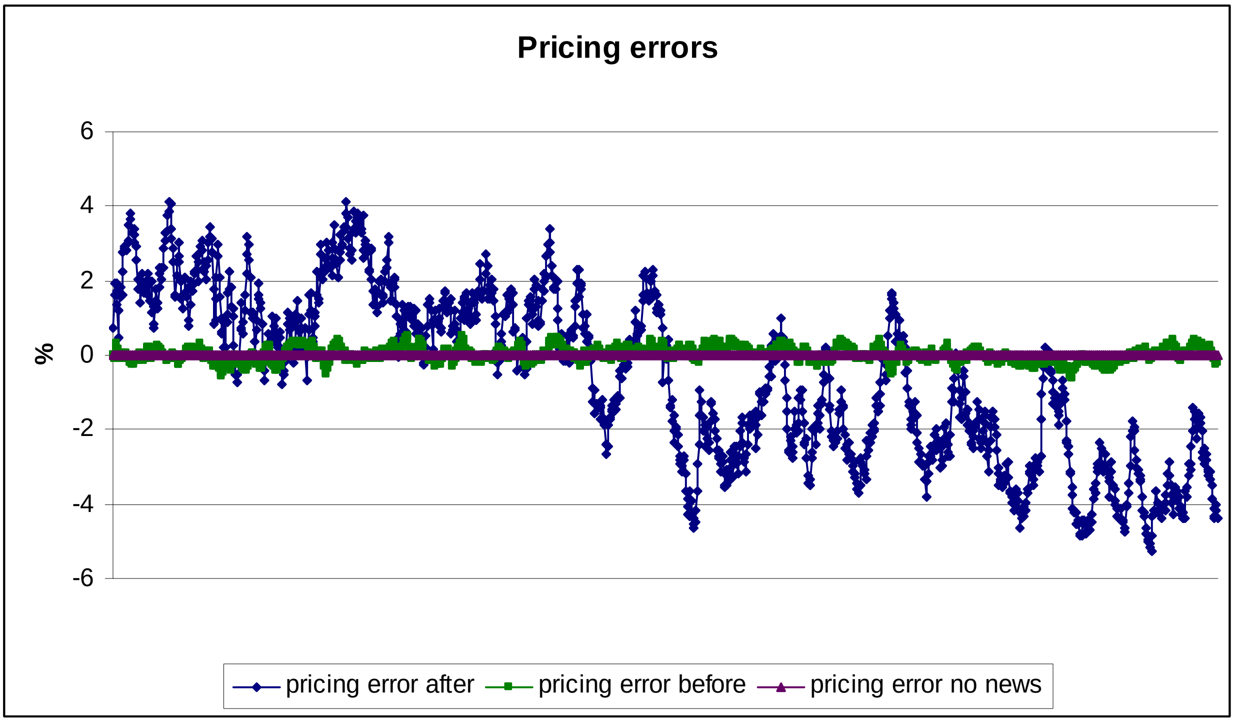


Figure 6. Estimated Pricing Errors

This figure displays the estimated one minute pricing errors for two symbols (ONE and AWE) from 10 A.M. to 3:30 P.M. for the days following M&A news, preceding M&A news and no-news days. Pricing errors are expressed in percent.



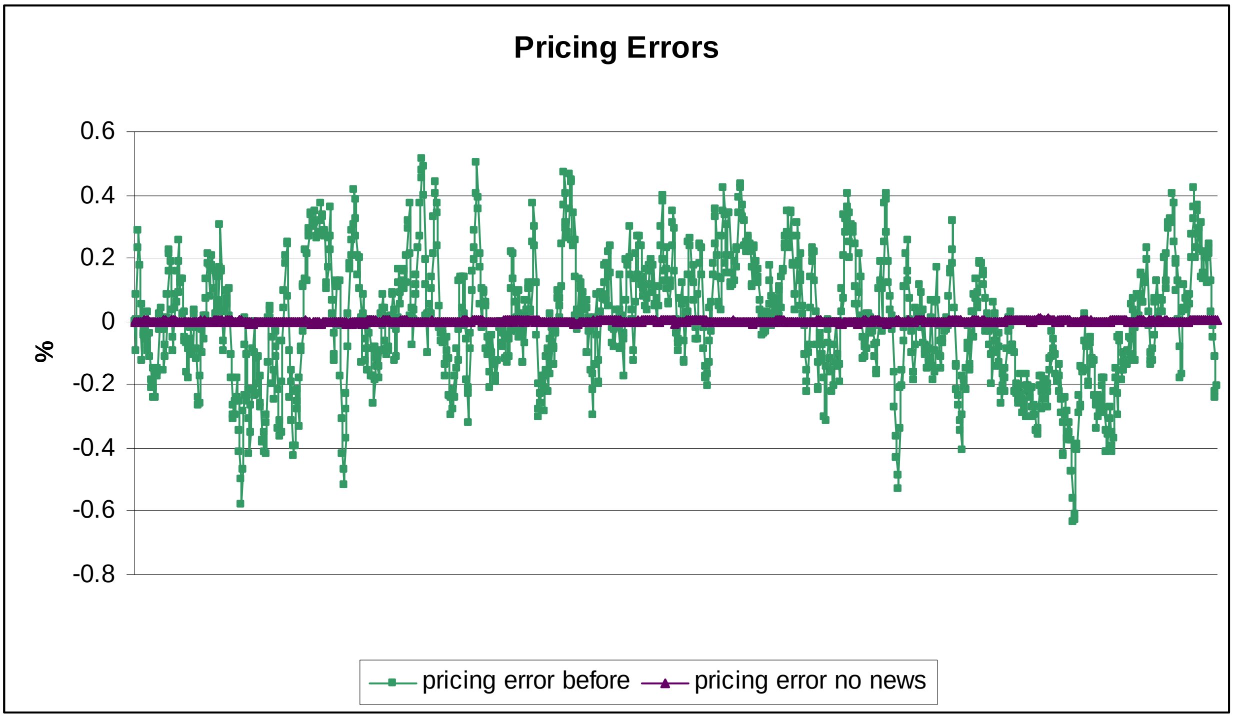
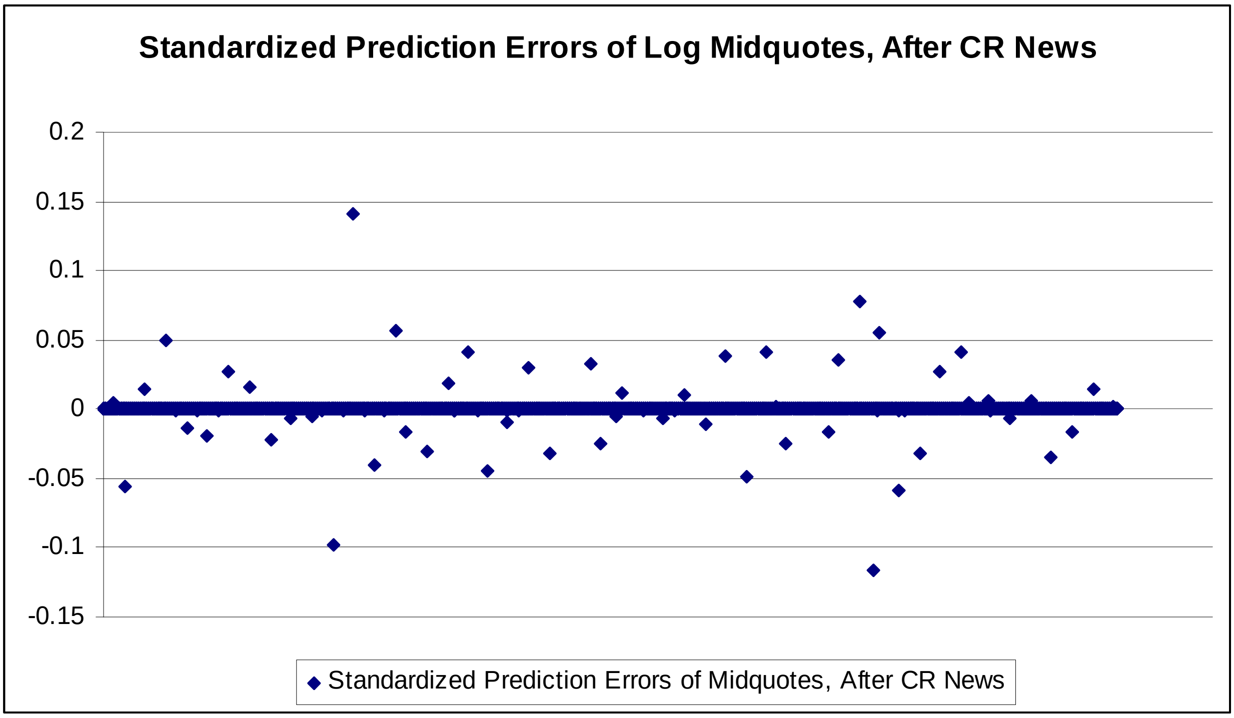


Figure 7. The Scatter Plots of the Standardized Prediction Errors for the "After" Sample

This figure displays scatter plots of the standardized errors of log midquote and normalized Lee-Ready order imbalances for days following merger news.



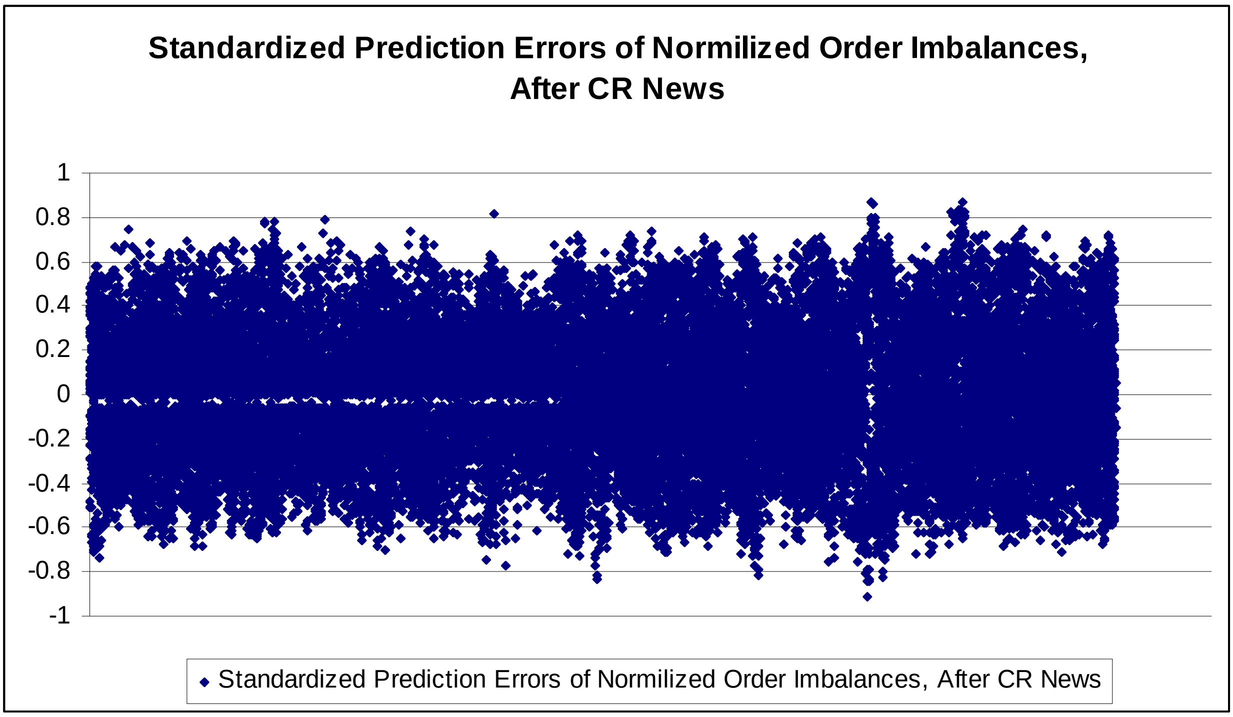
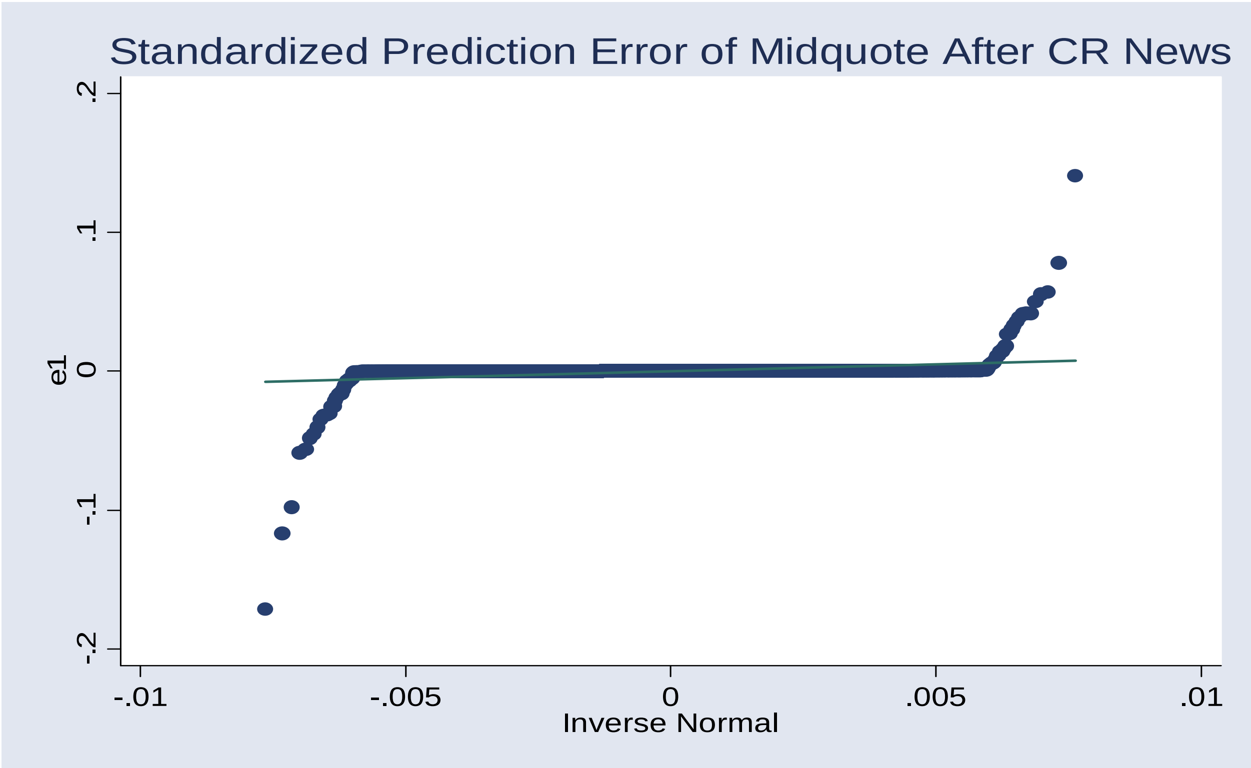


Figure 8. Quintile Plot of the Standardized Errors for the "After" Sample

This figure shows normal distribution quintile plot of the standardized errors of log midquotes and the Lee-Ready order imbalances in the "After" sample



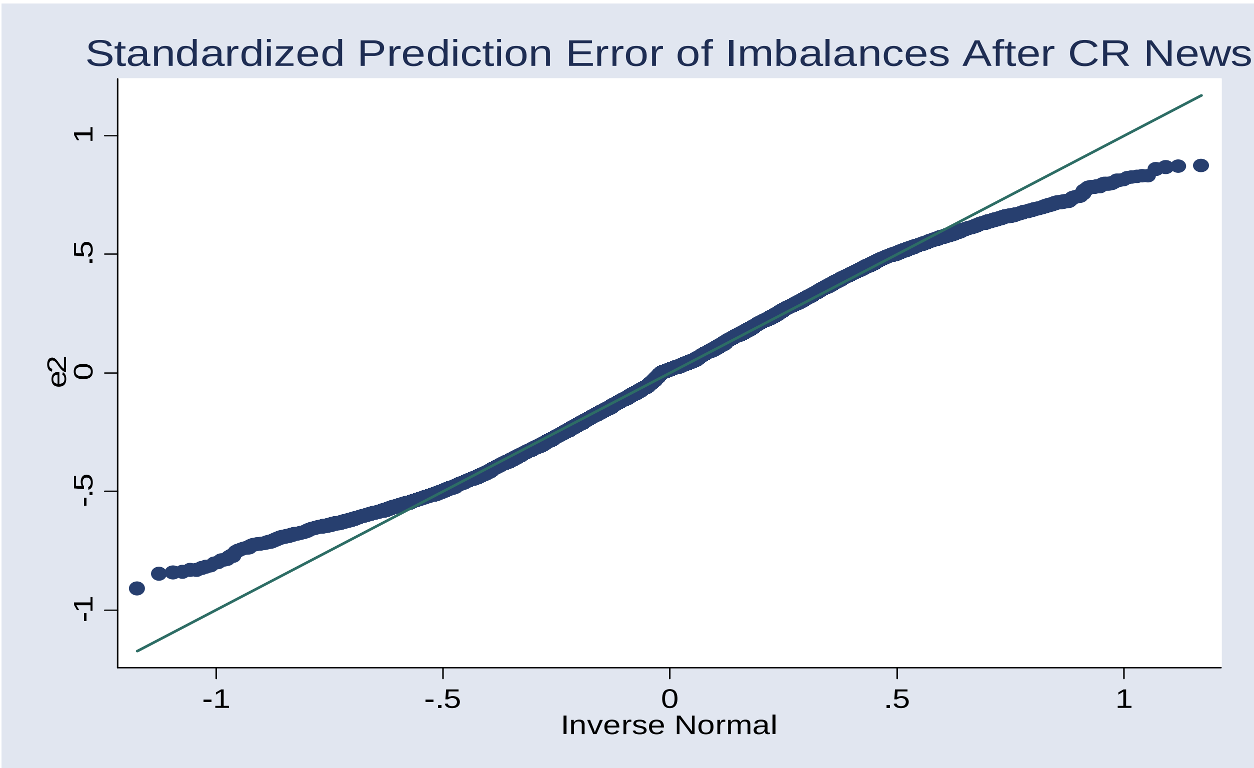
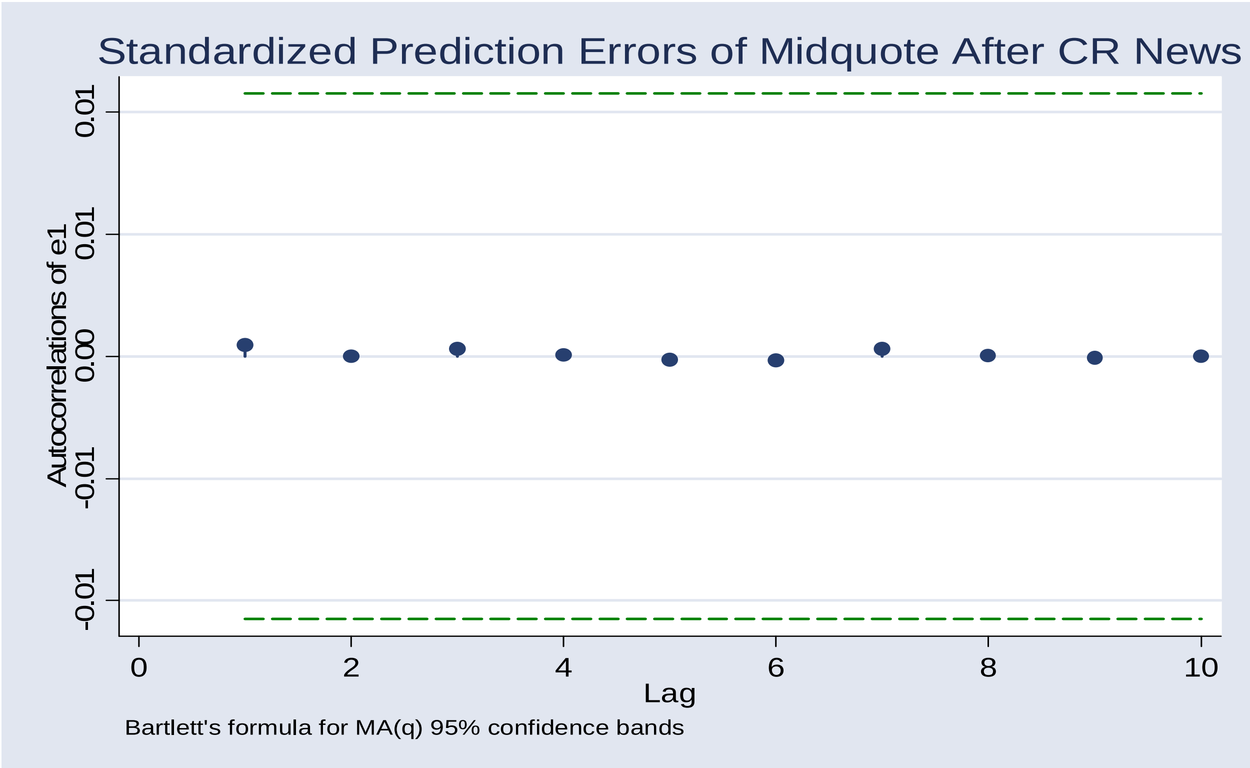


Figure 9. Correlogram of the Standardized Prediction Errors for the "After" Sample

This figure displays correlograms of the standardized prediction errors of log midquotes and the Lee-Ready order imbalances in the "After" sample. The charts show autocorrelations up to 10th lag and display 95% confidence intervals.



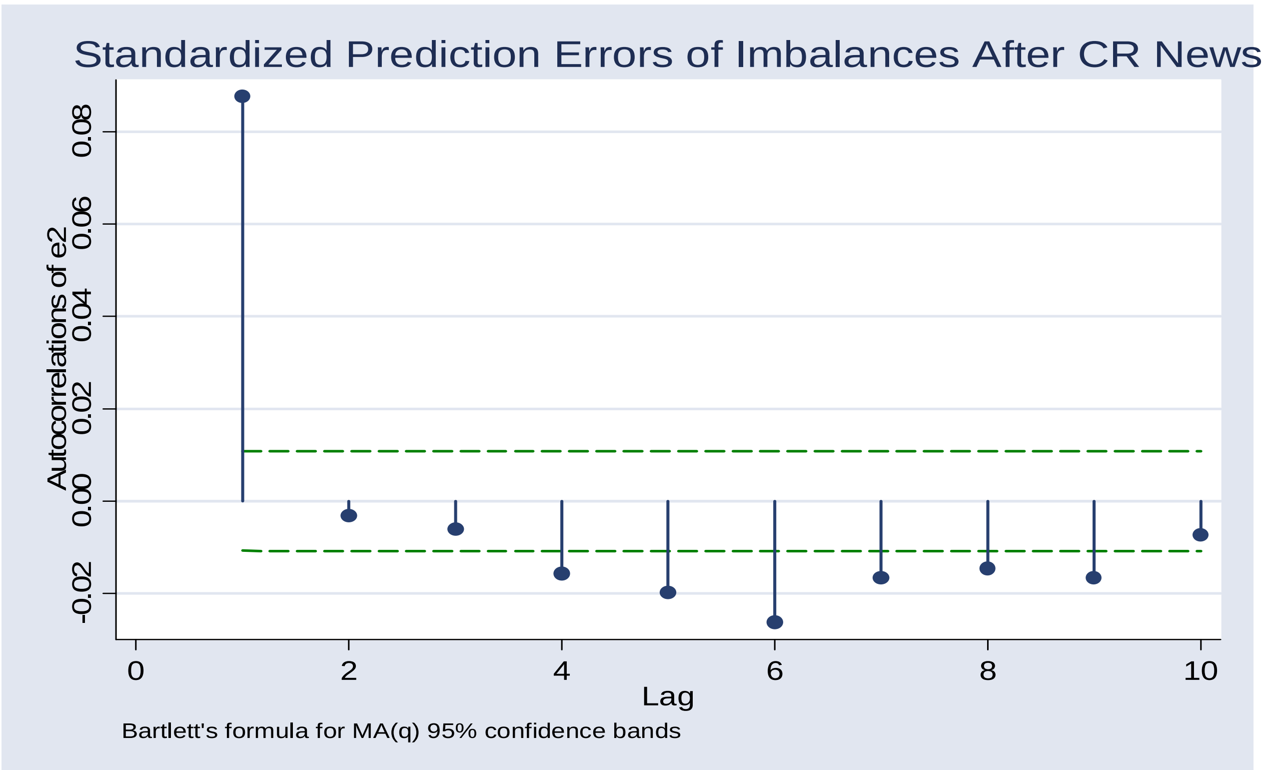


Figure 10. Cross-Correlogram of the Standardized Prediction Errors for the "After" Sample

This figure displays cross-correlograms of the standardized prediction errors up to 10th lag in the "After" sample.

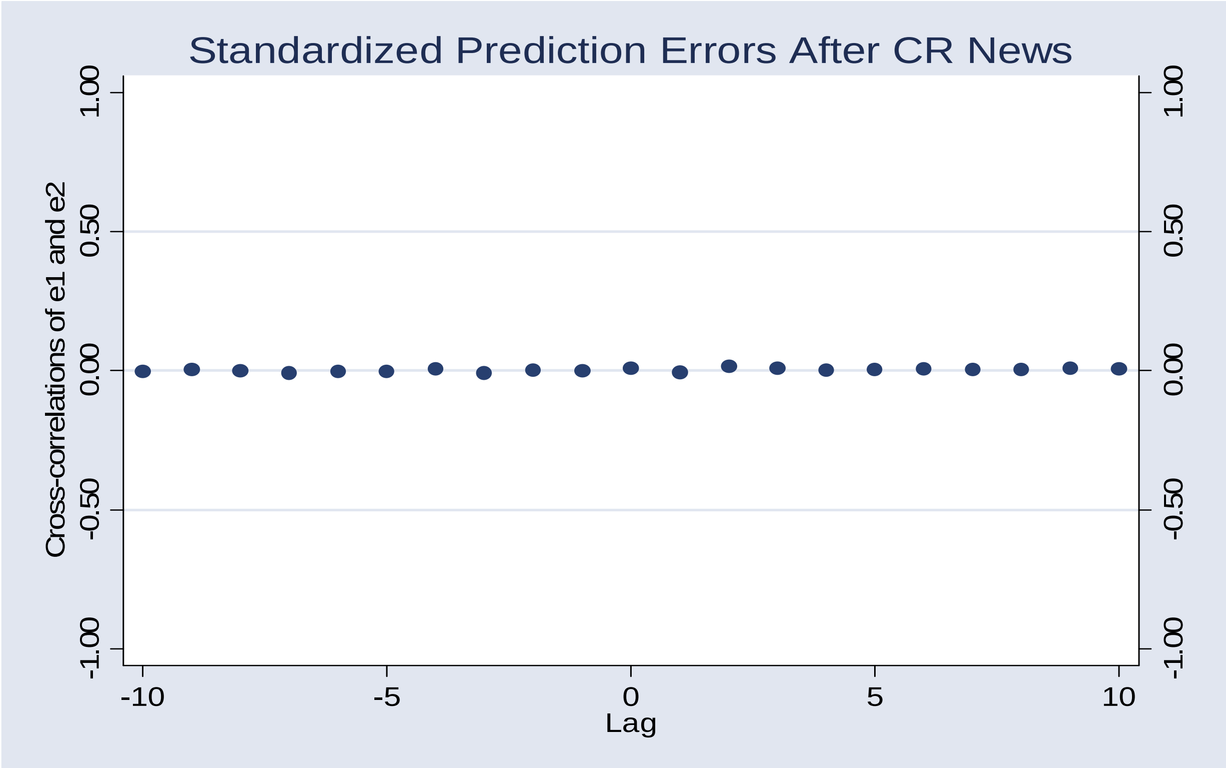
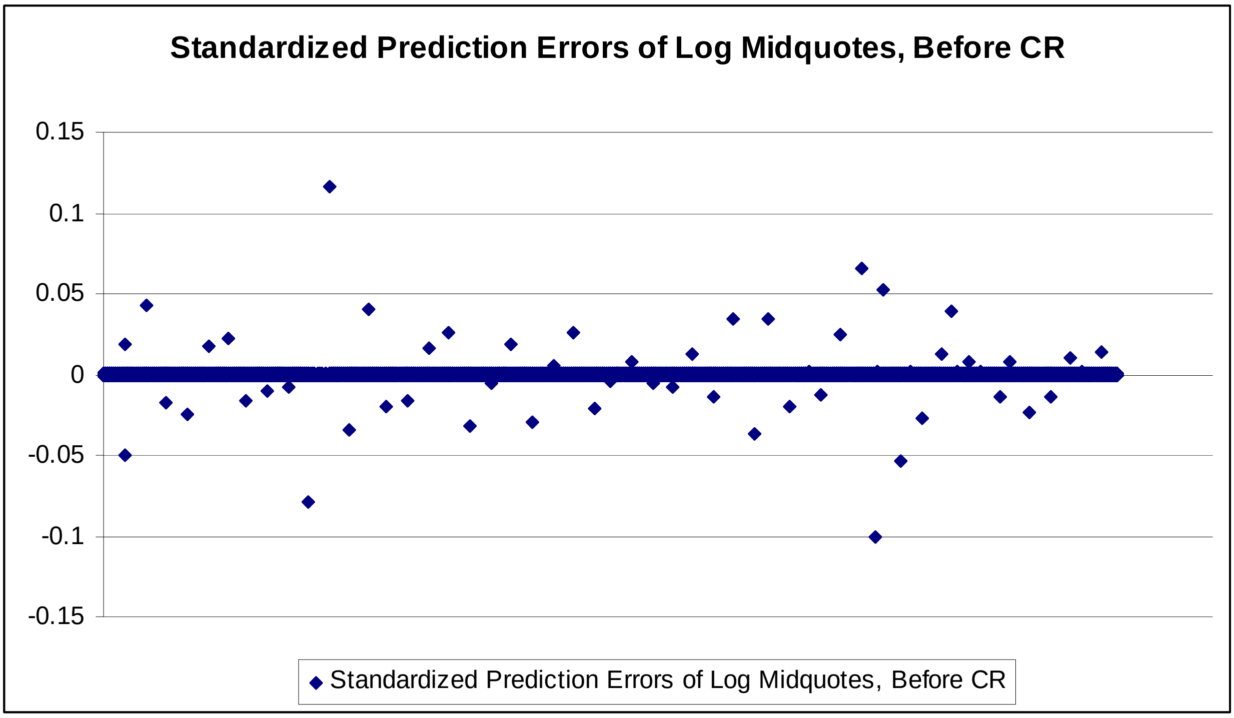


Figure 11. The Scatter Plots of the Standardized Prediction Errors for the "Before" Sample

This figure displays scatter plots of the standardized errors of log midquote and normalized Lee-Ready order imbalances for days before merger news.



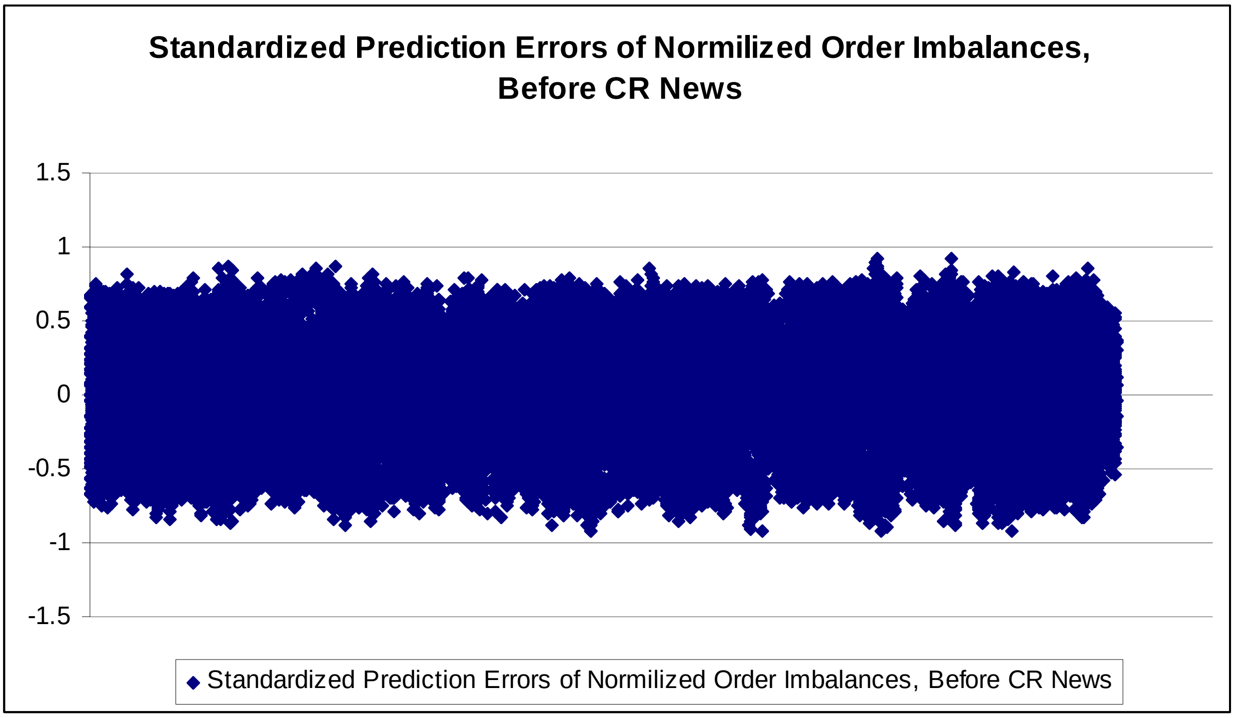
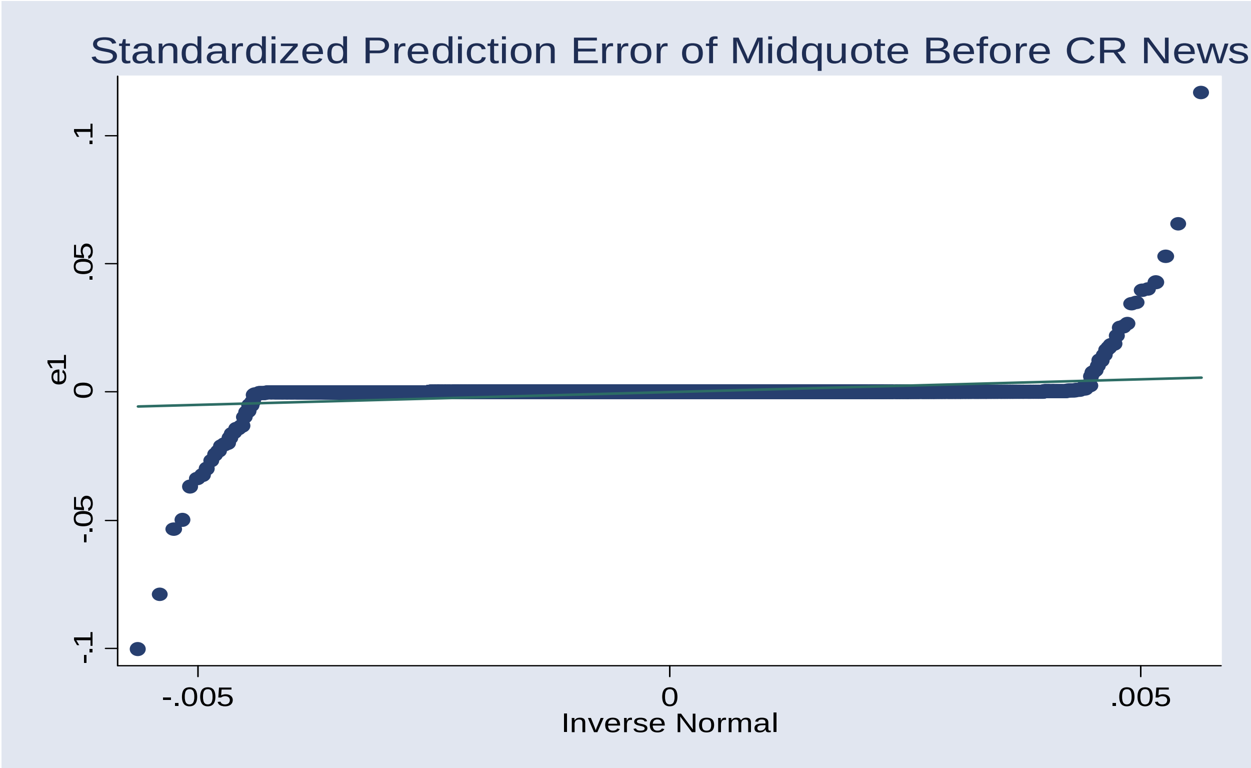


Figure 12. Quintile Plot of the Standardized Errors for the “Before” Sample

This figure shows normal distribution quintile plot of the standardized errors of log midquotes and the Lee-Ready order imbalances in the “Before” sample



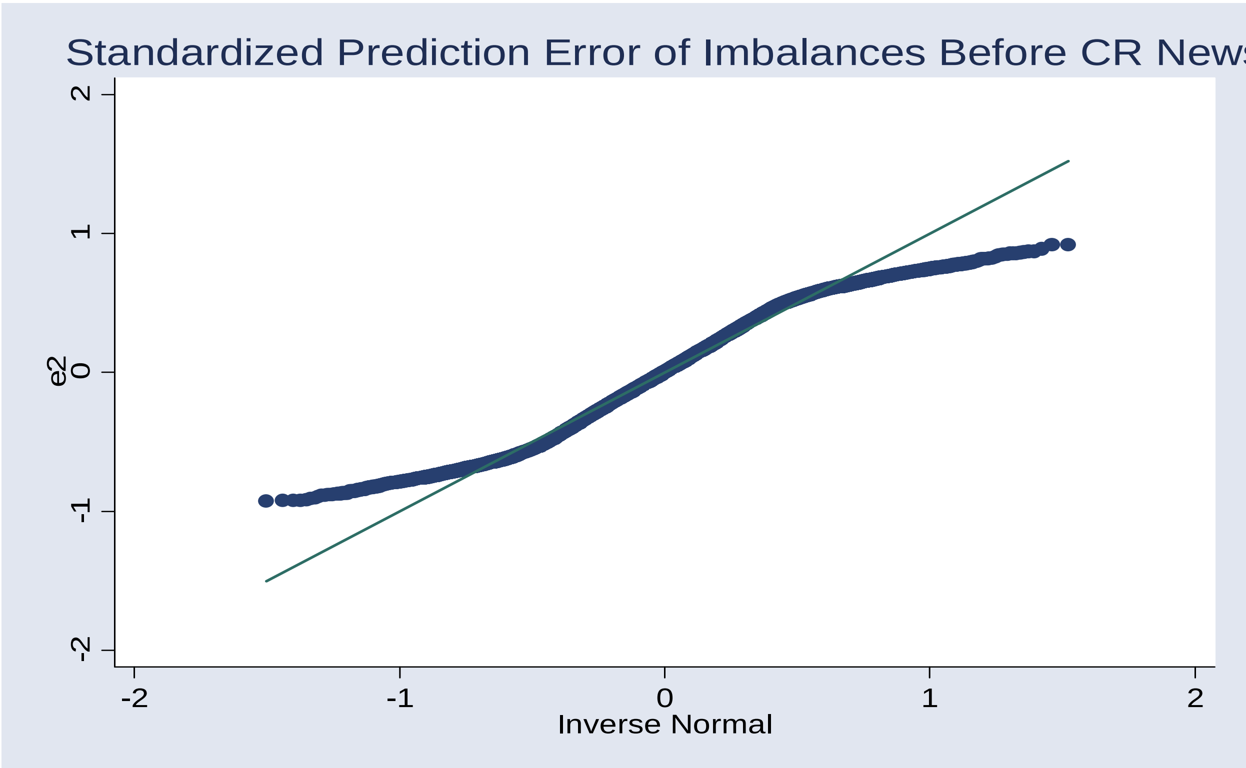
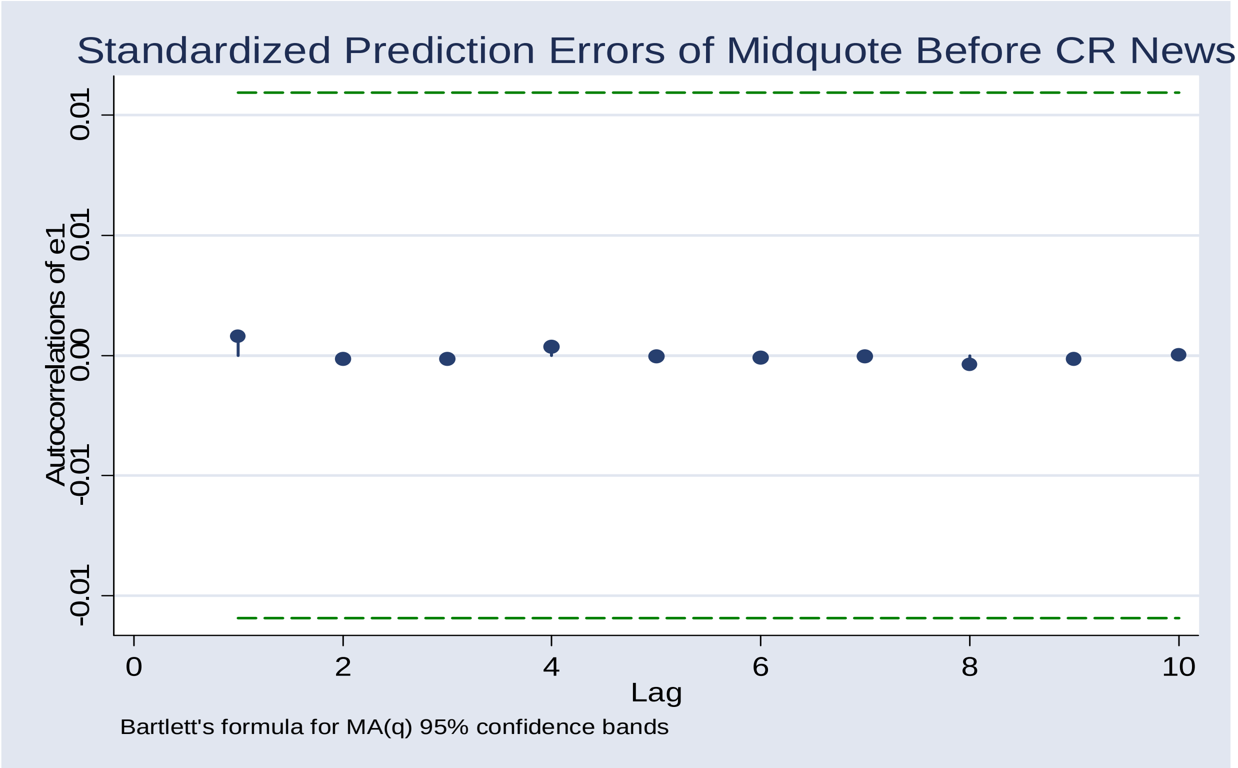


Figure 13. Correlogram of the Standardized Prediction Errors for the "Before" Sample

This figure displays correlograms of the standardized prediction errors of log midquotes and the Lee-Ready order imbalances in the "Before" sample. The charts show autocorrelations up to 10th lag and display 95% confidence intervals.



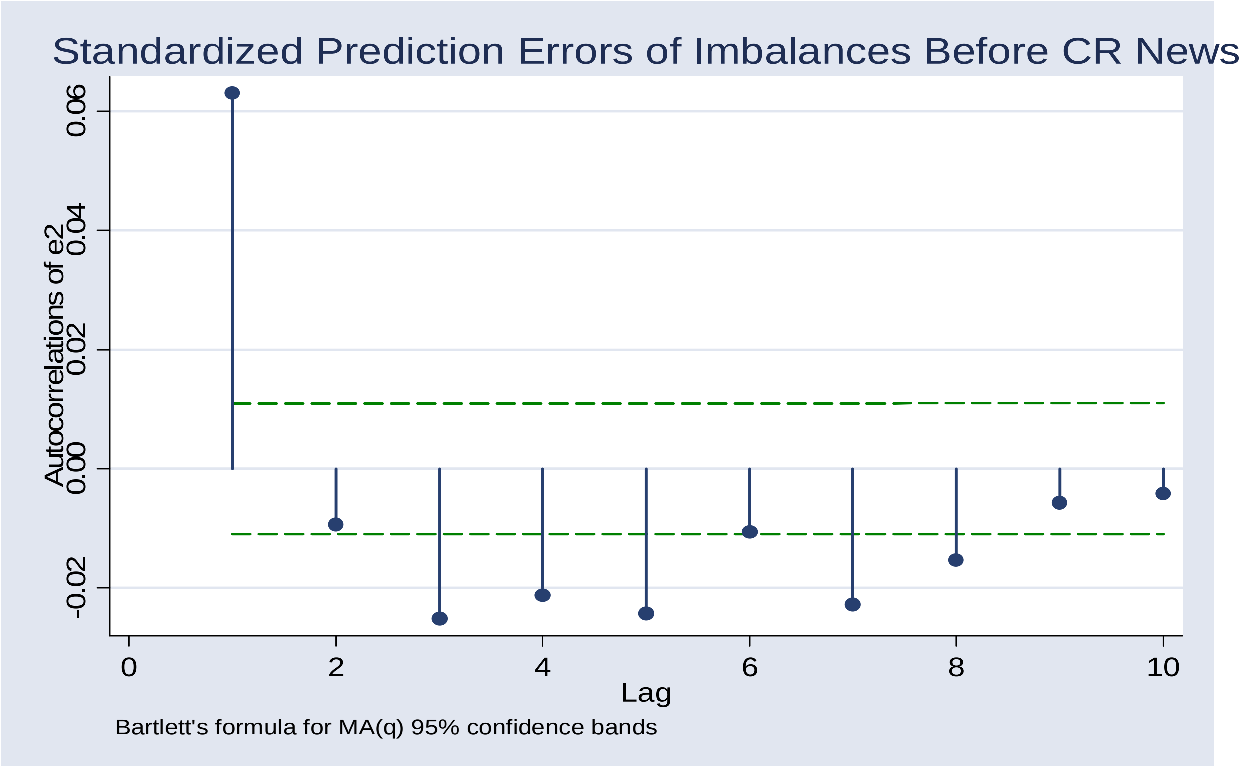


Figure 14. Cross-Correlogram of the Standardized Prediction Errors for the "Before" Sample

This figure displays cross-correlograms of the standardized prediction errors up to 10th lag in the "Before" sample.

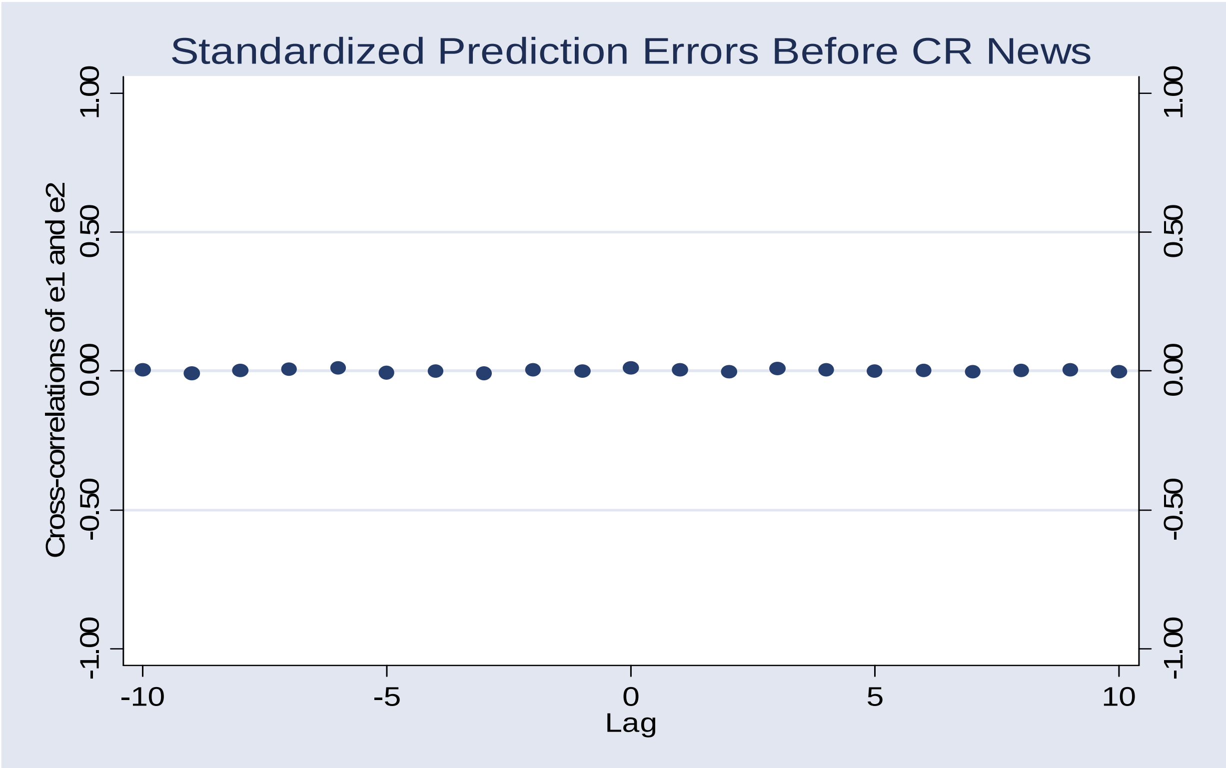
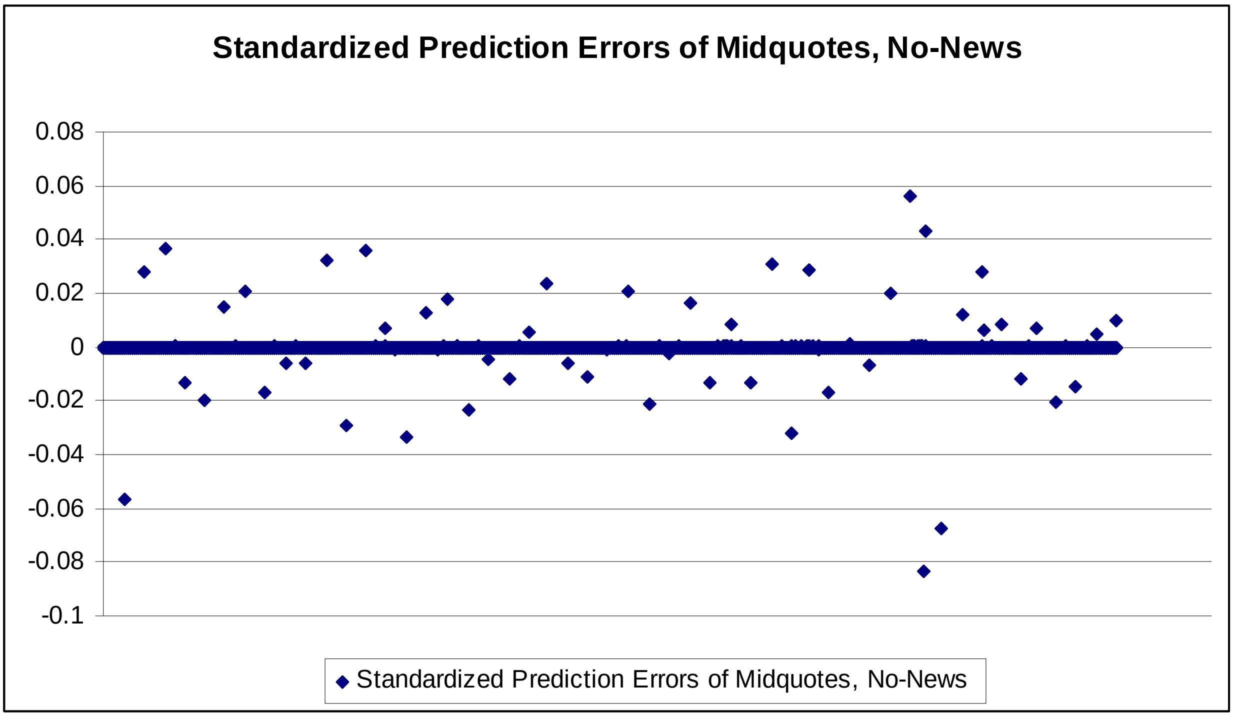


Figure 15. Scatter Plots of the Standardized Prediction Errors for “No-News” Sample

This figure displays scatter plots of the standardized errors of log midquote and normalized Lee-Ready order imbalances for “No-News” days.



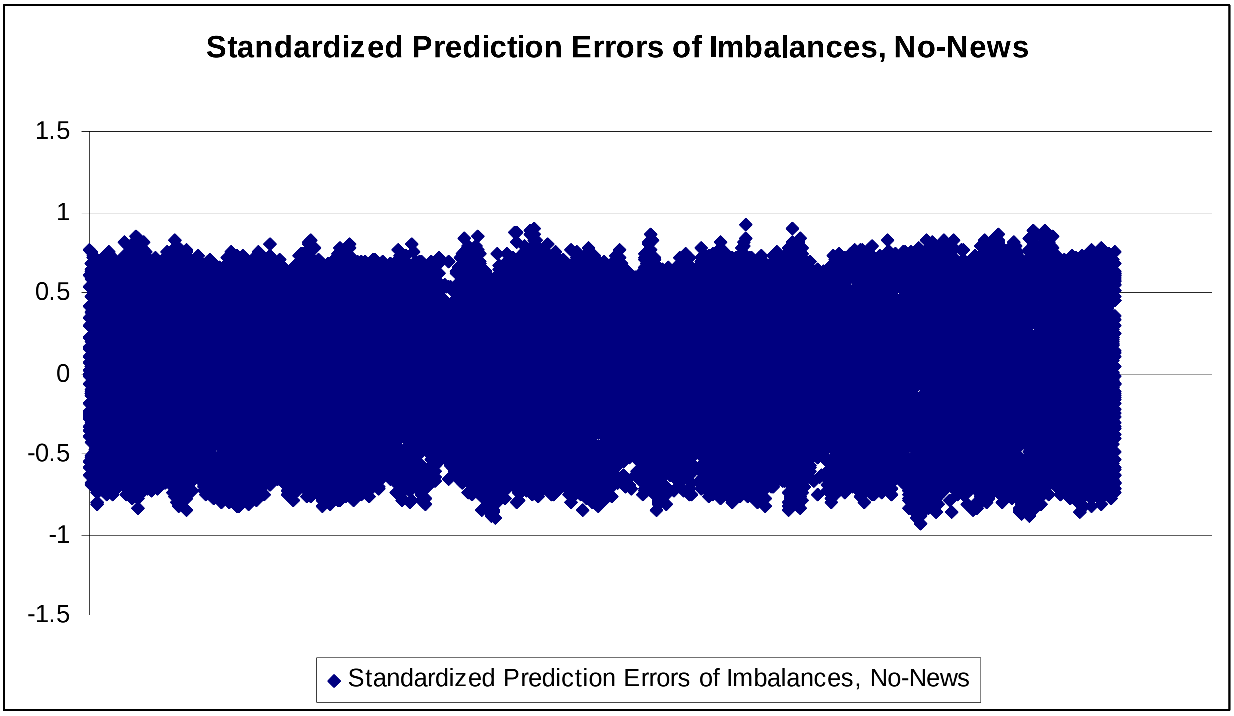
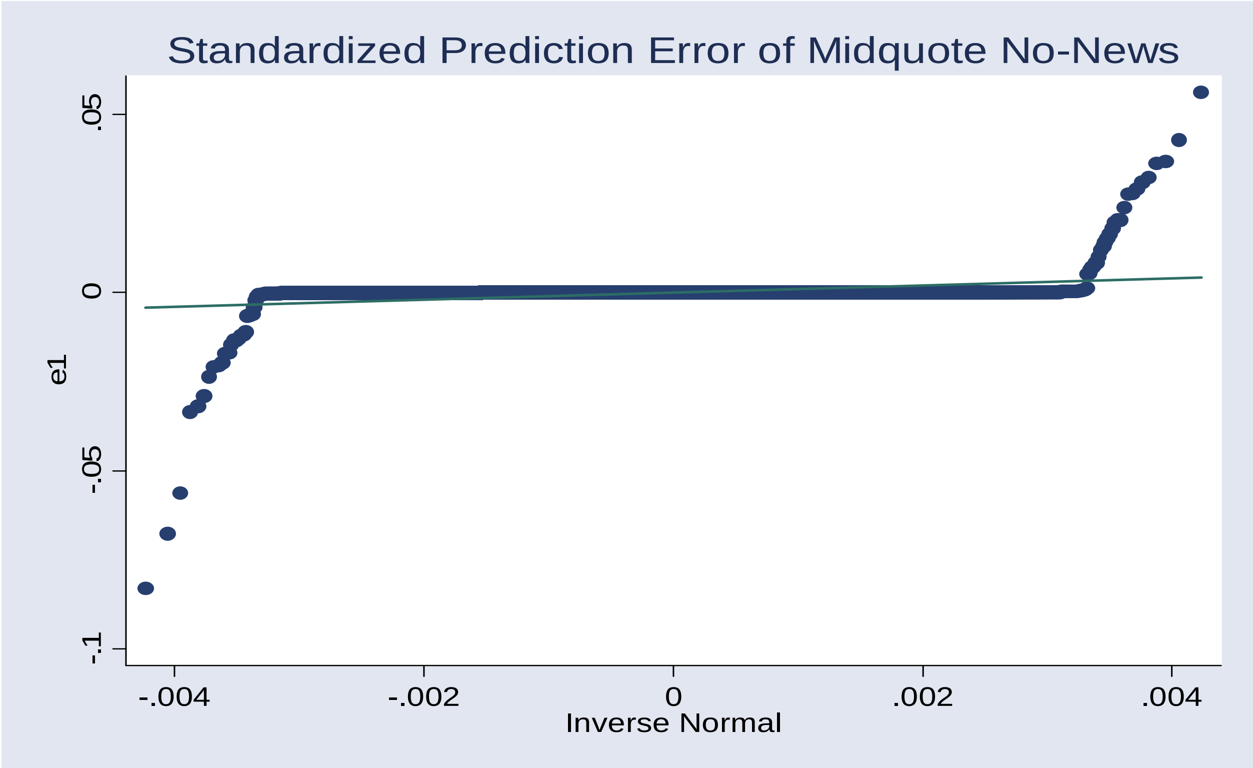


Figure 16. Quintile Plot of the Standardized Errors for "No-News" Sample

This figure shows normal distribution quintile plot of the standardized errors of log midquotes and the Lee-Ready order imbalances in the "No-news" sample



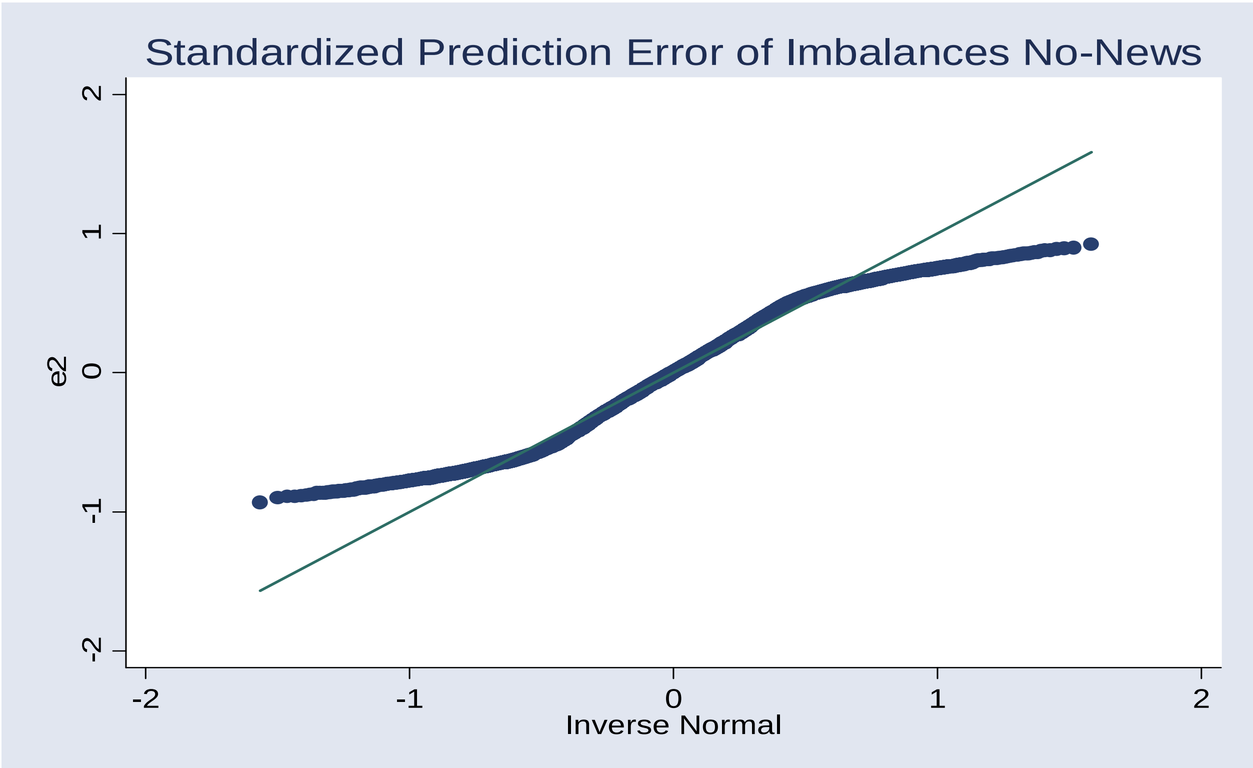
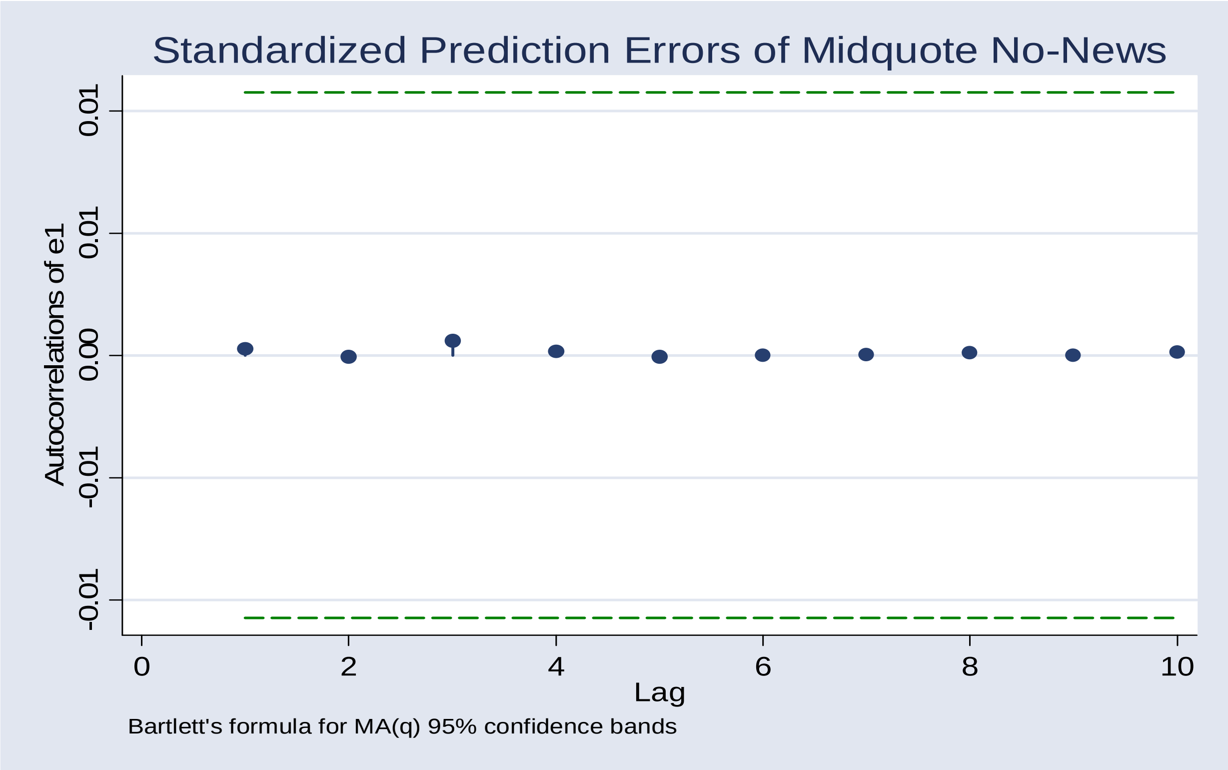


Figure 17. Correlogram of the Standardized Prediction Errors for "No-news" Sample

This figure displays correlograms of the standardized prediction errors of log midquotes and the Lee-Ready order imbalances in the "No-News" sample. The charts show autocorrelations up to 10th lag and display 95% confidence intervals.



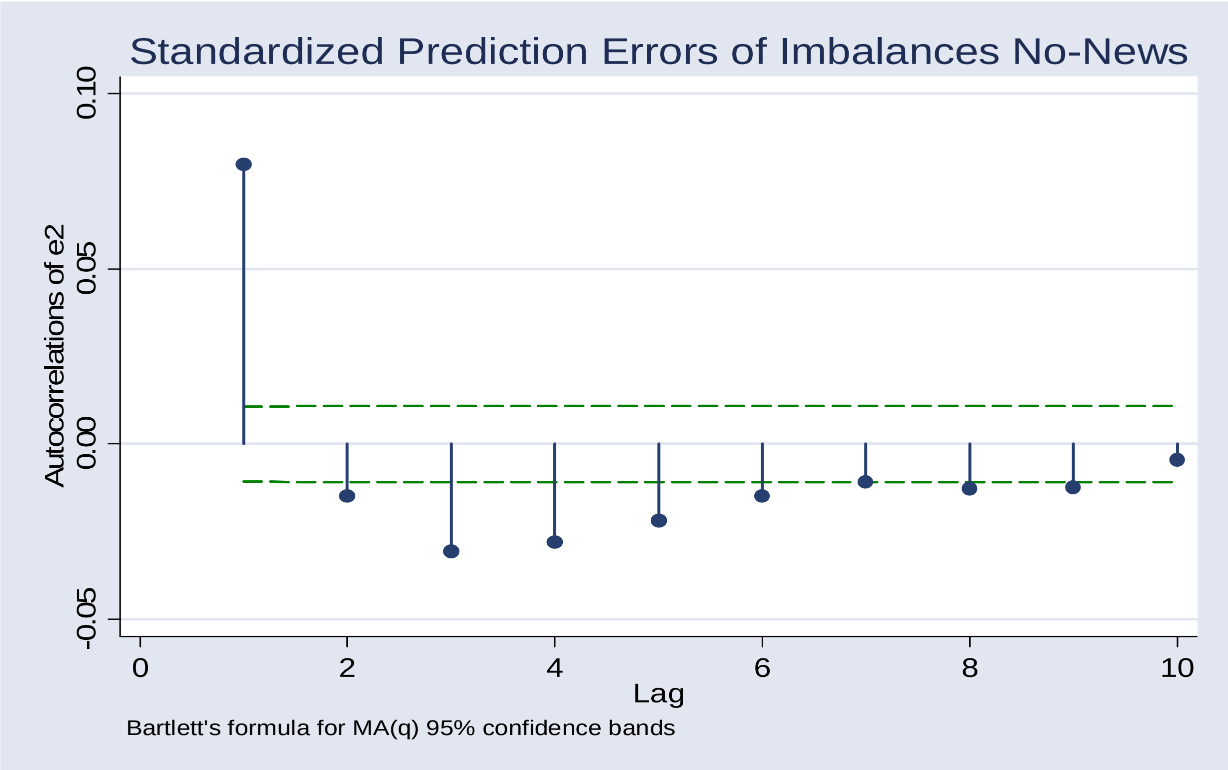
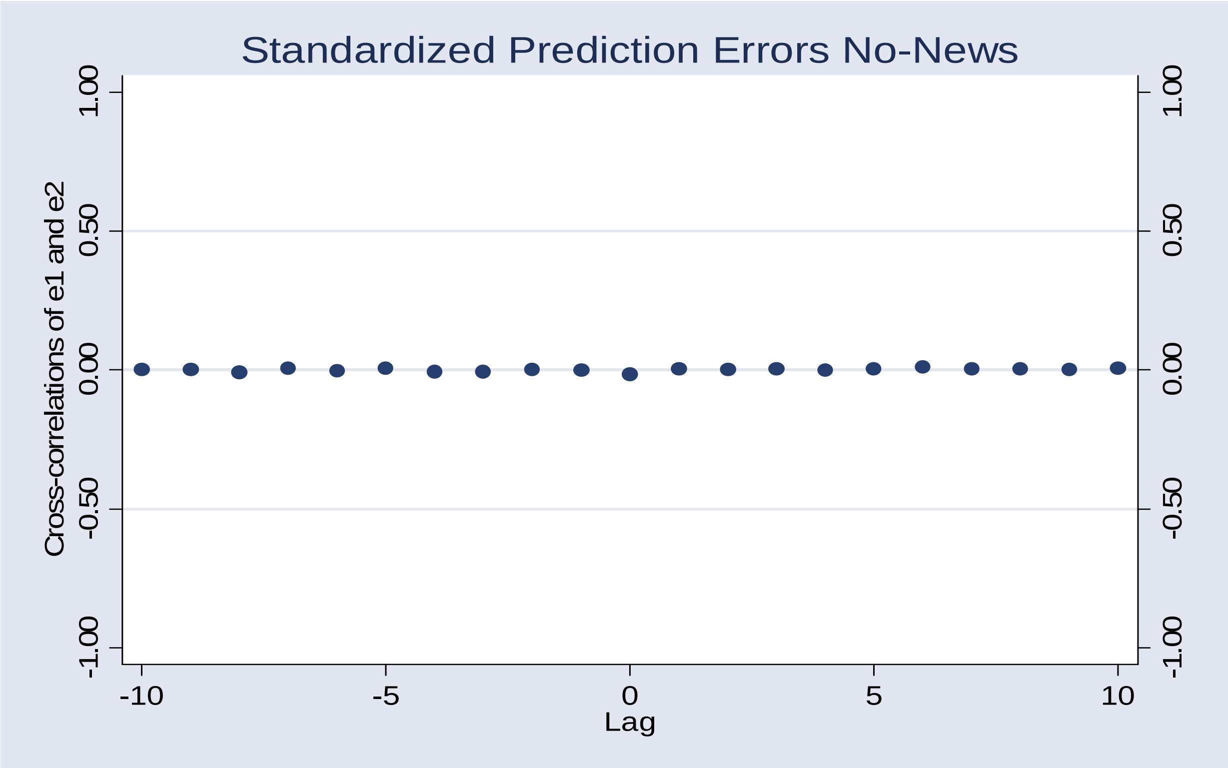


Figure 18. Cross-Correlogram of the Standardized Prediction Errors for "No-news" Sample

This figure displays cross-correlograms of the standardized prediction errors up to 10th lag in the "No-News" sample.



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