THE ACCURACY OF FINANCIAL ANALYSTS

AND MARKET RESPONSE

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ABSTRACT

Financial analysts play an intermediary role in financial markets, resulting in two steps for information to be fully absorbed into the stock price: analysts' reaction to information, and investors' reaction to analysts' recommendations. Thus any observed inefficiency in stock pricing could result from two possibilities: analysts failed to fully incorporate the market information into their stock analysis, or the information released in the analysts' report is not fully believed by investors.

The documented optimism of financial analysts may suggest the possibility of the later case. To test the accuracy of analysts from another perspective, we follow a market microstructure model and use intraday market data to estimate the probability of an information event, the probability of good or bad news, and the rates that different traders arrive at the market.

By comparing those estimates based on days with and without recommendation changes, we find inconsistent results with regard to a difference in the probability of an information event. For some stocks, we do observe an increase in the likelihood of news on days when analysts change their recommendations, but this is not the case for most stocks. However, even though they are inaccurate most of the time, uninformed investors usually believe financial analysts. Furthermore, it seems that uninformed investors disbelieve analyst recommendation changes at those instances when analysts are most accurate.

Because of this, we hypothesise that market makers might suspect that orders in the opposite direction of an analyst's recommendation change are more likely to come from informed traders. This is consistent with the intuition that most traders are uninformed and will simply follow the advice of a perceived expert, and therefore those that

don't follow that advice may be more likely to have special information of their own. We check whether there are any differences in the probability of information-based trading (PIN) and for the conditional probability of information-based trading conditioned on sell (PIN|sell) and buy (PIN|buy) between days with and without recommendation changes. We did not find any significant difference, indicating that although we may observe a higher arrival rate of informed traders on recommendation change days, the probabilities of information-based trading do not change substantially. More informed traders seem to come to the market merely because the higher arrival rate of uninformed traders on recommendation days gives them a good opportunity to camouflage their behaviour. And the specialists likely would not have to change their behaviour on those days by increasing or shifting bid-ask spreads since the increased costs from the higher volume of informed trading are balanced by increased profits from the higher volume of uninformed trading.

Furthermore, regression of the probabilities of informed trading (conditional or unconditional) on firm size, trading volume, and volatility of daily return shows nothing significant, so we weren't able to identify influential factors that affect informed trading or explain differences in informed trading between firms.

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Alpha (α)	The probability that an information event has occurred before the start of a trading day
a_t	The ask price set by the specialists
B	The number of buy-initiated trades on a trading day
B_1	The event that a trader wants to buy from the market maker
Beta (β)	The unconditional probability of a "good-news day"
b_t	The bid price set by the specialists
Delta (δ)	The conditional probability that the information event that occurred is bad news (a low signal)
Epsilon buy (ε_b)	The arrival rate of uninformed buy orders
Epsilon sell (ε_s)	The arrival rate of uninformed sell orders
Gamma (γ)	The probability of a "bad-news day"
Mu (μ)	The arrival rate of informed trade
S	The number of sell-initiated trades on a trading day
S_1	The event that a trader wants to sell to the market maker
Theta (θ)	The vector of the parameters

CHAPTER 1

INTRODUCTION

Analysts are those financial professionals who collect and evaluate the information related to a firm's future performance and in turn release their findings in research reports. They produce corporate earnings forecasts, write reports on individual companies, provide industry and sector analyses, and issue stock recommendations. Academic researchers have been interested in the function analysts provide to the financial market for a long time. However, "few issues in finance are more puzzling than the role played by financial analysts", as Easley et al. (1998) said. What we know for sure is that more than 3,000 sell-side analysts are currently working in the United States, not including associates and other junior analysts that provide research support (according to Jegadeesh et al. 2004); and each year they spend hundreds of millions of dollars on their analysis activities.

There are two main types of analysts: sell-side analysts and buy-side analysts. Sell-side analysts are those employed by a broker or dealer firm that manages client accounts and serves individual and institutional investors; and buy-side analysts are those employed by money management firms or institutional investors (mutual funds, for example). However, in most cases, only the recommendations from sell-side analysts are made available to the public. They place stocks on a "buy" list, disseminate written reports, and make recommendations to appropriate clients, whereas recommendations from buy-side analysts will be executed immediately as part of the investment strategy of their own companies, and are not shared with the public. Furthermore, buy-side analysts often use the reports from sell-side analysts as an input into their decision process. Following previous academic research, in this thesis we only consider sell-side analysts.

This chapter includes two sections: Section 1 discusses the optimism of financial analysts observed in the literature and the possible motivations for doing that; and Section 2 introduces the motivation for this research and the methodology we used for analysis.

1.1 OPTIMISM OF FINANCIAL ANALYSTS

1.1.1 THE ACCURACY OF ANALYSTS

Jensen and Meckling (1976) suggest that security analysts are socially productive for the role they play in reducing agency costs associated with the separation of ownership from control. This hypothesis was supported by empirical evidence given by Moyer et al. (1989). Further affirmation came from an extensive literature in the 1980s, (for example, Brown and Rozeff (1978), Collins and Hopwood (1980), and Givoly and Lakonishok (1984)), demonstrating that analysts' earnings forecasts are more accurate predictors of future earnings than univariate time-series models or other naïve forecasts. More recently, Frederickson and Miller (2004) disclosed that analysts assess stock prices more accurately than non-professional investors when both pro forma and GAAP earnings are available.

Unfortunately, several studies in the 1990s on the accuracy of analysts failed to find consistent results. The optimistic bias in the forecast error of the EPS has been widely documented. Francis and Philbrick (1993) argued that analysts make optimistic forecasts to maintain relationships with company managers. Clayman and Schwartz (1994) attributed the positive bias to analysts' tendency to "fall in love" with their stocks, proposing that investment banking relationships and the prospect of being cut off from access to company managers make issuing negative or critical reports difficult for analysts. Dreman and Berry (1995) established the persistent presence of an optimistic bias in analysts working in the U. S. market between 1974 and 1991 and found no significant differences in this optimism among industries or economic cycles. Olsen (1996) ascribed the positive bias and lack of accuracy in earnings estimates to herding behaviour among forecasters. The same persistent optimism has been documented for equity markets in the United Kingdom (Capstaff et al. 1995; De Bondt and Forbes 1999), Germany (Capstaff et al. 1998), and Europe (Capstaff et al. 2001).

On the contrary, a handful of studies recently failed to reject unbiasedness and efficiency in analyst forecasts after "correcting" methodological flaws or assuming non-standard analyst loss functions (see Basu and Markov 2004). Brown (2001) found that the mean and median forecasts during the 16 years from 1984 to 1999 indicate a shift from analyst optimism toward analyst pessimism. Abarbanell and Lehavy (2003) reported that median forecast errors are most often zero and the percentage of apparently pessimistic errors is greater than the percentage of apparently optimistic errors in the cross-section. They also identified an empirical link between firms' recognition of unexpected accruals and the presence of forecast errors, suggesting that firms' reporting choices play an important role in determining analyst forecast errors.

A similar confusing story happened with stock recommendations. Womack (1996) found that investment strategies based on following analyst advice typically yielded a return on investment that is higher than average. Wijmenga (1990) documented that while there is no significant long-term abnormal return to the stock recommendations, abnormal returns are very significant for the week of publication, and short-term abnormal returns are more pronounced for strong recommendations. Barber et al. (2001) found U.S. sell-side analysts' stock recommendations have significant value for the 1986-96 period: A portfolio composed of the most highly recommended stocks generated an average annual market-adjusted return of 3.97 whereas a portfolio of the least favoured stocks yielded an average annual market-adjusted return of –9.06 percent, a difference of more than 13 percentage points. On the other hand, contradictory evidence is found by Barber et al (2003) when data from year 2000 and 2001 are included: the stocks least favoured by analysts earned an average annualized market-adjusted return of 13.44 percent whereas the stocks most highly recommended underperformed the market by –7.06%, a return difference of more than 20 percentage points.[1] Jaffe and Mahoney (1999) reported that common stock recommendations in investment newsletters do not beat passive benchmarks. Yazici and Muradoglu (2002) showed that published investment advice does not help small investors. Jegadeesh et al. (2004) warned that naive adherence to analyst stock recommendations can be costly.

1.1.2 ANALYSTS' INCENTIVES

The documented inaccuracy of analysts gives rise to greater concerns for academic researchers. Dreman and Berry (1995) expressed a puzzle in the persistent nature of large forecasting errors, which is unlikely to be observed if analysts learn from past mistakes as rational decision makers are expected to do. They called for a "behavioural

[1] In spite of this, for the longer 1986-2001 period, the most highly recommended stocks still generated significantly greater average annual market-adjusted returns than did those least favoured (2.44 percent as compared with –9.94 percent).

explanation” with the question “Is it possible that the ‘best’ analysts' judgmental forecasts may not be the ‘best’ forecasts career wise?” They suggest that an estimate far off the consensus might pose career dangers, whereas an estimate near the consensus may provide the analyst with a much higher degree of safety, regardless of how inaccurate it may prove to be. Olsen (1996) supported this by showing that analysts who otherwise would tend toward a below-average forecast are drawn toward the mean and are unwilling to fully reflect the negative view in their forecasts because the market appreciates an optimistic outlook. Hong and Kubik (2003) concluded that after controlling for accuracy, analysts who are more optimistic than the consensus are more likely to experience positive career moves.

Might it be that analysts purposely overstate a stock’s valuation to attract public attention to promote the underwriting business of their companies? This possibility, called analysts’ misaligned incentive, attracted the attention of academic researchers and regulators, especially during the 1990s. During that time, analysts became an integral part of Wall Street profit centers, thus obtaining the name “Age of the Analysts” on Wall Street by Nocera (1997). Thus the effect of investment banking relationships on analysts’ stock recommendations has been studied empirically. Dugar and Nathan (1995) showed that financial analysts of brokerage firms that provide investment banking services are more optimistic in their earnings forecasts and investment recommendations, compared to non-investment banking analysts. Lin and McNichols (1998) found that lead and co-underwriter analysts' growth forecasts and recommendations are significantly more favourable than those made by unaffiliated analysts, although their earnings forecasts are not generally greater. Michaely and Womack (1999) showed that “buy” recommendations by underwriter analysts perform more poorly than those by unaffiliated brokers. This is true prior to, at the time of, and subsequent to the recommendation date, so they concluded that the recommendations by underwriter analysts show significant evidence of bias. These studies provide evidence consistent with the belief that brokerage houses reward optimistic analysts who generate investment banking business and trading commissions.

However, this is not accepted by all researchers. Analysts cherish their reputation for forecasting expertise because the expertise in earnings forecasts and stock picking are the two most important criteria for each year's *Institutional Investor ranking of money manager*. The top three vote getters in each industry are called All-American, and a high ranking in this poll will benefit the brokerage houses greatly by increasing the influential ability among the buy-side analysts. Analysts also benefit directly through bonuses and salary increases, so it is hard to believe that they would want to sacrifice accuracy, or at least they will be very careful in their choice between an upward-biased forecast to promote their firm's investment business and being accurate to improve their own reputation.

1.2 MOTIVATION AND METHODOLOGY

Taking into consideration the intermediary role that financial analysts play in securities markets, there are two steps for information to be fully absorbed into the stock price: The first one is analysts' reaction to information and the second is investors' reaction to analyst recommendations. This is particularly relevant when markets have many investors who feel uncertain about their decisions because the economic environment is sufficiently complex for them. They usually choose to turn to financial analysts, who have the expertise to make more precise estimates, for advice and guidance. Thus any observed forecast errors could result from two possibilities: analysts fail to fully incorporate relevant information into their stock analysis, or the information released in the analysts' report is not fully believed by the investors. Either will lead to inefficient pricing of securities, although a simultaneous failure of both may not. We can think of these as either a direct failure or a perceived failure to properly gather or analyse information.

With the documented optimism of financial analysts, one may argue that joint failure is likely, at least for positive recommendations. That is investors are sceptical about the incentives of analysts, so do not fully believe what analysts recommend, which tends to be overly optimistic.[2] Brown (1996) argued using indirect evidence that investors rely too little on analysts' earnings forecasts, instead of too much as claimed by Dreman and Berry (1995). Morgan and Stocken (2003) modeled a financial market containing a firm, a sell-side equity analyst, and many investors who are uncertain of the motivations of the analyst. Assuming that the market is efficient and investors are risk neutral, the firm's stock price equals the firm's expected value given all publicly available information; the payoff to the analyst is composed by two parts: the benefit associated with his/her ability to inflate the stock price above its true value to generate investment banking business, and the cost associated with poor performance which will harm his/her poll ranking, they showed that investors' uncertainty about their incentives makes it impossible for an analyst to credibly reveal good news about a firm's valuation, even when the analysts' incentives are perfectly aligned with those of investors. Only for unfavourable reports could all relevant information be impounded into the stock price.

[2] This is still the case even with the efforts of the Securities Industry Association who released "Best Practices" guidelines to enhance analyst credibility, since "… the guidelines are good, but that they have no teeth; … Moreover, most of the firms that signed on say they already conform largely -- or completely -- to what the guidelines lay out, and plan only moderate policy changes." (By Jeff D. Opdyke "Guidelines Aim to Polish Analysts' Image". *Wall Street Journal*; Jun 13, 2001. p. C.1).

More uncertainty about the accuracy of analysts could exist after the effectiveness of Regulation Fair Disclosure[3] (Reg FD) on October 23, 2000, which prohibits the selective disclosure of material information to financial analysts. Since then, financial analysts only have access to public information that is available to all investors, so it is quite possible that their information is different from the information of truly informed insiders, leading to more doubt from investors and market makers.

Since the studies from return perspective done in the previous literature could not tell us whether it is inaccurate analysts' reaction to information and/or improper investors' reaction to analyst recommendation, in this thesis, we test the accuracy of financial analysts from another perspective by using a market microstructure model. Investors often need to complete their transactions on an exchange, and exchanges like the New York Stock Exchange (NYSE) are characterized by specialists who carry inventory and make a market by buying and selling each particular stock. The behaviour of these market makers may reveal to us some information about the quality of analyst recommendations.

Models about the specialists that are relevant to our study started with Glosten and Milgrom (1985), who modeled a market with trades occurring according to the following sequence: The specialist sets bid and ask prices. An investor arrives and is informed of the bid and ask prices. He is free to buy at the ask or sell at the bid or just leave. After he has made a decision, the specialist is free to (and generally will) change the bid and ask prices at any time before the next arriving investor. Suppose that the specialists know the true value of the stock will be either low (V_d) or high (V_u), they will set bid and ask prices as

[3] Securities and Exchange Commission, Regulation FD, Code of Federal Regulations 243, 100-243.103.

$$a_1 = E[v|B_1] = V_d \Pr\{V = V_d|B_1\} + V_u \Pr\{V = V_u|B_1\}$$

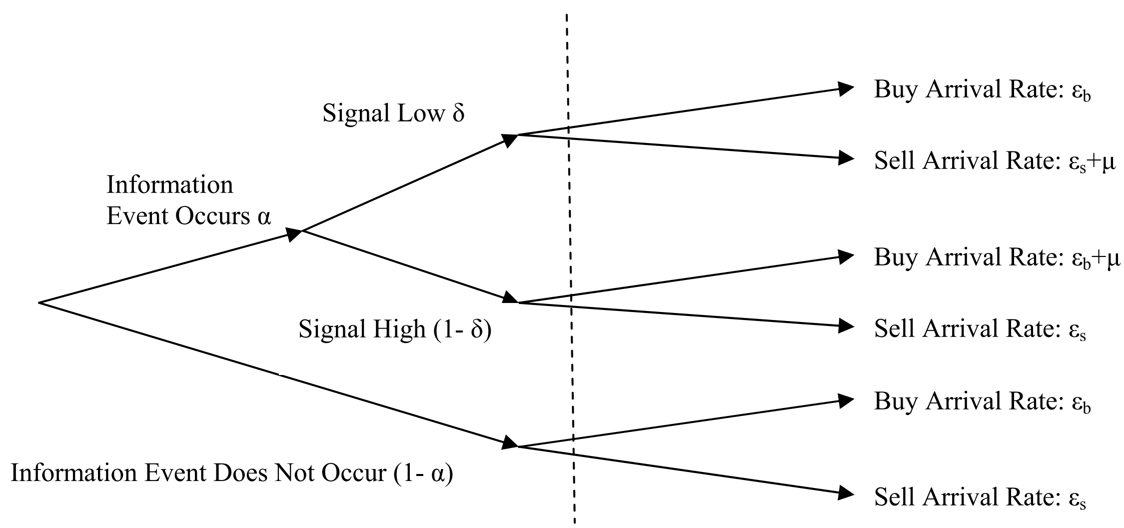
$$b_1 = E[v|S_1] = V_d \Pr\{V = V_d|S_1\} + V_u \Pr\{V = V_u|S_1\} \quad (1.1)$$

where S_1 denotes the event that a trader wants to sell to the market maker and B_1 the event that someone wants to buy from the market maker. They illustrated that solving the adverse selection problem gives rise to the bid-ask spread. The bid-ask spread is the sum of the so-called "lemons discount" and “peach premium”. If the "lemons discount" and the “peach premium” are symmetrically distributed, the mid price is equal to the average full-information price (Garleanu and Pedersen 2004). However, with intervention from financial analysts, the specialist may value the “lemons discount” and “peach premium” asymmetrically. For example, he may give a larger discount for the bid price and a smaller premium for the ask price when financial analysts make a “buy” recommendation, in which case the midpoint price would be lower than the full-information price, which could be interpreted by the market as financial analysts being overly optimistic.

Easley et al. (2002) give a structural model based on the sequential trade tree diagram shown in Figure 1 (More details are given in Chapter 2). This allows us to observe a particular sequence of trades and work backwards to discover information about the underlying structural parameters. In our research, we add a third class of traders into the model, *analyst followers*, who base their trades on analyst recommendations. Including this third class of trader will allow the market maker to observe an increase in trading volume on days when analysts change their recommendations without necessarily increasing his assessed likelihood that an information event has occurred.

The approach involves using intraday market data and assessing whether the transactions recorded are initiated by buyers or sellers. The arrival of the various investor types is modeled as following Poisson processes. The structural parameters including information event probabilities and the arrival rates of different traders are estimated using a maximum likelihood technique and are compared on days with and without recommendation changes. Furthermore, based on the estimated parameters, the unconditional and conditional probabilities of information-based trading on days with and without recommendation changes can be estimated and compared.

Figure 1: Tree diagram of the trading process



α is the probability of an information event, δ is the probability of a low signal, ε_b is the arrival rate of uninformed buy orders, and ε_s is the arrival rate of uninformed sell orders, and μ is the arrival rate of informed trade. Nodes to the left of the dotted line occur once per day.

The remainder of the thesis is organized as follows. Chapter 2 provides a comprehensive review of the literature on market microstructure, the asymmetry between bid and ask prices; the difference between informed and uninformed traders and the information content of analyst recommendations. Chapter 3 discusses the methodology and data in detail. Chapter 4 presents the results of empirical tests and analyses the findings. The conclusions are summarised in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews the findings of previous studies on areas relevant to this thesis. Section 1 provides a review of literature on market microstructure, focusing on the information content of trades. The first part of this section discusses what kind of information the trade process has, and the second part talks about empirical methodology used in the model of information-based trading. Section 2 discusses the asymmetry between bid and ask prices. Section 3 reviews studies on informed and uninformed traders, supporting the notion that financial analysts are not informed traders. Section 4 documents the literature about the information content of analyst recommendations.

2.1 INFORMATION CONTENT OF TRADES

Information[4] is the most important factor when traders formulate their expectations of stock value. Akerlof (1970) shows that asymmetric information, a situation where agents are differently informed and some may even have superior information, concerns the financial market. People are suspicious that they may purchase a stock from a better-informed seller. Since the better-informed owner would be unwilling to sell at a price lower than the fundamental value of the stock, it is likely that the buyer has paid too

[4] Information is defined by Henri Theil as a change in expectations about the outcome of an event, Economics and Information Theory (Chicago and Amsterdam: Rand McNally and North Holland Publishing Company, 1967), Ch.1.

much. Awareness of the existence of this information asymmetry leads investors to value information greatly and to widely pursue it in the market.

With the notion of rational expectations equilibrium (REE), Danthine (1978) illustrated that in a situation where agents are heterogeneously informed, all the relevant information will finally be aggregated in the equilibrium price and is revealed freely to all market participants. This corresponded to what Fama (1970) described as strong form market efficiency where the prices fully reflect all public and private information. However Grossman and Stiglitz (1980) questioned the possibility of an informationally efficient market: if the equilibrium price will freely reveal all of the information, why should traders expend resources to obtain private information? If no traders are interested in obtaining information, there is no way that the equilibrium price can be an information aggregator and transmitter. This is a vicious cycle. Besides, the assumption in REE that market participants understand the environment in which they operate and are able to extract all the information concealed in the equilibrium price looks too strong for the real world.

A more practical situation is one where some, but not all, information will be aggregated and transmitted by the equilibrium price, described in the literature as a "noisy rational expectation equilibrium", where the incentive to collect information remains (Diamond and Verrecchia 1981). Thus, how new information is incorporated into prices via interaction of informed and uninformed traders or how the true value is discovered through the trading process, leads to a branch of financial economics known as "market microstructure".

"Market microstructure" terminology was first used by Garman (1976). Since then, there has been a sizable increase in research on it, characterized by "theoretical rigor and extensive empirical validation using new databases" (Madhavan and Panchapagesan, 2000). Schwartz (1988) defined it as "focused on the details of the trading process. The major elements of this process include the generation and dissemination of information, the arrival of orders, and the rules, institutions, and other design features of a market that determine how orders are transformed into trades". Although market microstructure has broader interest in topic, information is particularly emphasized in the theory. The central concept is that the trade itself conveys information, and the continued trading of the informed traders provides at least the potential for the other uninformed market participants to infer the underlying information.

In microstructure models, the key to understanding the dynamics of price adjustment is the Bayesian learning model. This model was first implemented to microstructure by Conroy and Winkler (1981), dealing with how the market maker learns new information from the arrival and composition of trades. Market makers play a passive role by adjusting quotes of bid and ask prices in response to changing conditions in the market. In a Bayesian learning model, the market maker (and other uninformed traders) does not know what the "true" value of the asset is. What he must do is infer this true value using the indirect evidence from the order flow. Suppose he has a prior belief about the asset value. Then he observes the market data and based on this data he calculates the conditional probability that a particular event has occurred. This conditional probability is his posterior probability of the event, and it incorporates the new information he has learned from observing the trade. This is an updating process which continues with the posteriors eventually converging to the true value.

2.1.1 INFORMATION FROM A TRADE PROCESS

Although the learning process is simple to understand, the order flow from which the market maker infers the true value of the asset (as mentioned above) varies in the literature. For example, in Glosten-Milgrom's (1985) model, it is the type of the next trade that matters, i.e. a buy or a sell; in Kyle's (1985) model, the market maker learns from the net imbalance of buys and sells. Other information like total volume, transaction size, etc., has been studied as well.

A. Information Surprise

Glosten and Milgrom (1985) showed that someone wishing to buy causes the market maker to revise his expectation of the asset's value upward and his quotes accordingly; and someone wishing to sell causes the market maker to revise his expectation and quotes downward. In Kyle's (1985) model, the market maker in a market with sequential auctions simply acts as an order processor, observing net order imbalance (the accumulation of signed orders) in one auction period, setting a price equal to his new expectation of the asset value, and then trading the quantity necessary at this price to clear the market. The assumption in both models is that buys and sells should be equally likely. So the imbalance of order flow actually serves as an information surprise to the market maker.

This was empirically supported. Hasbrouck (1988) examined the relation between trades and quote revisions for NYSE stocks and noted that if there were any private information inferred from a trade, it must be inferred from trade innovation, the component which was unanticipated, not from the total trade. Hasbrouck (1991) modeled the interactions of security trades and quote revisions by a vector autoregressive system in which the information content of a trade is measured by the persistent price impact of the trade innovation. They confirmed that market participants (including specialists) revise their information to incorporate an assessment of the conveyed information signal, and the stock price impact is increasing with the magnitude of the unexpected component of trading activity.

B. Trading Volume

Beaver (1968) initiated a stream of studies using volume to test investors' reactions to the release of information. He argued that the volume reaction to a new piece of information is due to the lack of consensus among investors and if consensus were reached, there would be no volume reaction, but only a price reaction. That is to say, the change of price reflects the average change in traders' beliefs, while volume reflects the extent of the differences in their beliefs. However, Verrecchia (1981) continued the study on earnings announcement event and found that the degree of volume reaction to new information cannot be used to infer the extent of agreement among investors about how that information should be interpreted, because a volume increase may indicate that investors interpret the information differently, or it may be that they interpret the information identically, but that information is quite different from their prior expectations. This is formalized in a model of trading volume developed by Karpoff (1986).[5] Besides, Verrecchia (1981) suggested that it is possible to combine volume reaction with price reaction to measure the extent to which information can change expectations.

Holthausen and Verrecchia (1990) identify two effects of information releases: an informedness effect measuring the extent to which agents become more knowledgeable,

[5] Volume is treated as the number of transactions between buyers and sellers in this model.

and a consensus effect measuring the extent of agreement among agents at the time of information release. They demonstrated that the unexpected price changes and trading volume are each influenced by both informedness and consensus effects, thus interpretations of unexpected price changes and volume associated with information releases are "conceptually similar". Following that, a number of event studies use trading volume to determine whether an event has "information content".

Empirical research also indicates that volume is negatively related to the bid-ask spread (see Cohen et al. 1979 for an early survey). Copeland and Galai (1983) said the bid and ask prices given by the market maker weigh the costs from informed traders to the revenues from uninformed traders. Several theoretical models consider the relation of trading volume to price change. Copeland (1976) derived a model with the assumption of sequential information arrival and demonstrated that by assuming the symmetrical distribution of optimists and pessimists, the absolute value of price changes and the expected number of trades show a positive correlation with a logarithmically increasing function. Another model considered price and volume in noisy rational expectations equilibrium and showed that the magnitude of the price change is uncorrelated with trading by speculators with private information but is positively related to trading by liquidity-motivated investors (see Karpoff 1986). So the strength of the correlation between absolute price changes and volume is negatively related to the existence of private information.

C. Trade Size

In Glosten and Milgrom's (1985) model, traders are assumed to buy or sell one unit of the asset each time. Easley and O'Hara (1987) weakened this assumption and allowed the traders to choose to trade with different quantities. They showed that due to the quantity bias that informed traders prefer to trade larger amounts at any given price relative to uninformed traders, market makers must also depend on the trade size when making their pricing strategy, because the larger the trade size, the more probable it is that they are trading with better informed traders, i.e. there is an increased probability of information-based trading.

Relevant to the relationship between trade size and the quality of information possessed, some studies showed that informed traders prefer to trade large amounts at any given price (Holthausen and Verrecchia, 1990, for example). Trade size is likely to be positively related to the quality of information possessed by them. Holden and Subrahanyam (1992) claimed that better-informed traders would trade more aggressively in order to obtain the benefits of private information before it becomes public. On the other hand, some models indicate that a monopolist informed trader may camouflage his trading activity by splitting one large trade into several small trades over time (Kyle 1985) or by trading when liquidity volume is high (Admati and Pfleiderer 1988). Barclay and Warner (1993) found that informed traders concentrate their orders on medium-sized trades. They proposed a "stealth trading" hypothesis stating that during a period of time, the informed traders attempt to camouflage their private information by engaging in multiple smaller trades rather than to achieve their desired portions by one or two larger trades. This hypothesis was supported by the results from the data of 105 NYSE firms that were tender-offer targets between 1981 and 1984. They concluded that trades motivated by private information are generally of medium size, defined as trades between 500 and 9,900 shares. Thus trade size will not necessarily convey adverse information. Besides, the relationship between adverse selection spread and the size of the trade is not agreed upon unanimously. Huang and Stoll (1997) provided evidence that adverse selection spread measures increases with raw size of the trade. In contrast, Heflin and Shaw (2005) argued that adverse-selection measures are not increasing with the raw number of shares traded, but with the trade size scaled by depth.

So, what kind of information does the trade process really provide? Jones et al. (1994) clarified that the relation between volume and volatility frequently analyzed in finance literature reflects the positive relation between volatility and the number of transactions in fact. They showed that the number of trades appears to provide virtually all the explanation for the volatility-volume relation, with trade size playing a trivial role. This is consistent with the finding of McInish and Wood (1991), who decomposed the volume into the number of trades and the number of shares per trade, and found that the number of trades is dominant in the relationship with returns. What is more intriguing is that Jones et al. (1994) claimed that more theoretical work is needed to determine which features of the trade process are indeed the information pertinent to the pricing of securities. This was then argued by Easley et al. (1997) by stating that in fact “what is needed is an empirical methodology for using the structure of existing microstructure models in empirical research” and then they developed such a framework to analyze the information in the trading process.

2.1.2 THE PROBABILITY OF INFORMATION-BASED TRADING

Easley et al. (1997) illustrated a technique to estimate the parameters in the Easley and O’Hara (1992) theoretical microstructure model from a time series of trade data. The theoretical model given by Easley and O’Hara (1992) involves a sequential trade model similar in spirit to Glosten and Milgrom (1985). The strength of a sequential trade model is that it allows the adjustment of prices to information to be analyzed on a trade-by-trade basis. In this model, the market maker is assumed to be risk neutral and competitive. Traders arrive individually at the market according to a probabilistic structure. Following each arrival, the market maker revises her quotes based on information revealed by the trading process. Figure 1 is a tree diagram of this sequential trading process.[6]

The probability that an information event has occurred before the start of a trading day is α. The new information is a signal regarding the underlying asset value, where good news occurs with a probability (1 – δ), leading the asset value to V_i^u and bad news occurs with a probability δ, leading the asset value to V_i^d. Trading is repeated over trading days $i = 1, \ldots, I$ as a game between the market maker and traders. On day i, trade begins with traders arriving according to Poisson processes throughout the day. Orders from uninformed buyers arrive at rate ε_b, and orders from uninformed sellers arrive at rate ε_s. Informed traders only buy if they have seen good news and sell if they have seen bad news. Orders from informed traders on information event days arrive at rate μ. The trading process is as follows: The market maker observes the trade, and uses this information to update his beliefs. Then new prices are set, trades evolve, and the price process moves in response to the market makers' changing beliefs.

Induced by this model, the likelihood function for a single trading day is

$$\begin{aligned} L(\theta | B, S) &= (1-\alpha) e^{-\varepsilon_b} \frac{\varepsilon_b^B}{B!} e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!} \\ &+ \alpha\delta e^{-\varepsilon_b} \frac{\varepsilon_b^B}{B!} e^{-(\mu+\varepsilon_s)} \frac{(\mu+\varepsilon_s)^S}{S!} + \alpha(1-\delta) e^{-(\mu+\varepsilon_b)} \frac{(\mu+\varepsilon_b)^B}{B!} e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!} \end{aligned} \tag{2.1}$$

[6] This is given in Easley et al. (2002), which is developed in a series of papers by Easley et al. (1997), Easley et al. (1998), and Easly et al. (2001).

where B and S represent total buy trades and sell trades for the day respectively, and $\theta = (\alpha, \mu, \varepsilon_b, \varepsilon_s, \delta)$ is the parameter vector. This likelihood is a mixture of distributions where the trade outcomes are weighted by the probability of it being a good-news day, $\alpha(1 - \delta)$, a bad-news day, $\alpha\delta$, and a no-news day, $1 - \alpha$. Assuming days are independent, the likelihood of observing the data $M = \{(B_i, S_i), i = 1, \ldots, I\}$ over I trading days is just the product of the daily likelihood function, that is

$$L(\theta|M) = \prod_{i=1}^{I} L(\theta|B_i, S_i) \tag{2.2}$$

where (B_i, S_i) is trade data for day $i = 1, \ldots, I$. Maximizing (2.2) over θ using the data set M provides a way to determine estimates for the underlying structural parameters of the model. The authors used GRADX from the GQOPT package to do the estimation and the likelihood function is well-behaved. Furthermore, the independence across trading days was tested and it failed to be rejected.

Based on those estimated parameters which are the "primitives" underlying the market-maker's learning and pricing problem, Easley et al. (1997) describe a technique to estimate the probability of information-based trading (PIN) as

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_b + \varepsilon_s} \tag{2.3}$$

This helps illustrate how the quotes and spreads are affected and how asymmetric information affects market behaviour. The economic use of these parameters was demonstrated successfully in Easley et al. (1997), Easley et al. (1998), Easley et al. (2001) and Easley, Hvidkjaer and O'Hara (2002).

Easley et al. (1997) incorporated trade size into the model as an extension. Denoting φ as the probability that an uninformed trader chooses to trade a large amount and ω

as the probability that an informed trader trades the large trade size, a more complex structure can be analyzed and estimated. Unfortunately, the likelihood statistics for the two models are almost identical, which suggests that trade size provides no additional information content. This is consistent with the findings mentioned above.

In Easley et al. (1998), the probability of information-based trading was estimated for two groups of stocks that differ in analyst coverage, i.e. high and low analyst following. Looking at the estimated parameters, the probability of a private information event, α, showed no statistical difference, thus the hypothesis that financial analysts discover information that otherwise would never become private information and make it possible for their clients to trade on this information to raise the probability of a private information event, is not supported. However analyst coverage does matter in the composition of trade where stocks with high analyst following have both higher rates of informed and uninformed trading. This is consistent with the notion that at least some clients of analysts act as uninformed traders. However, the probabilities of informed trading PIN for stocks with high and low analyst following are not different at the 0.05 significance level, demonstrating that the number of analysts is not a good proxy for information-based trade, although the estimated probability of informed trading does have significant explanatory power with respect to actual spread behaviour.

Easley et al. (2001) extend this empirical technique to examine the different hypotheses about stock splits. The estimated parameter from the model facilitated the investigation at the effects of stock splits----the changes in the trading strategies of investors and in the information environment of stocks. They assume that uninformed traders can use either market or limit orders but informed traders only use market orders, with γ_b and

γ_s as the fraction of uninformed limit buy and sell orders. In this case the probability of informed trading is

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_b(1-\gamma_b) + \varepsilon_s(1-\gamma_s)} \tag{2.4}$$

In a general case where $\varepsilon_b \neq \varepsilon_s$ and $\delta \neq 0.5$, they supported the trading range hypothesis, which predicts an increase in uninformed trade when stocks split by showing that the mean percentage change of trading rate of uninformed buyers ε_b is highly statistically significant. However the information asymmetry hypothesis was not supported because the probability of informed trading (PIN), which represents the extent of the adverse selection problem, did not show a significant decrease as predicted.

Easley et al. (2002) investigated the role of information-based trading in affecting asset returns by incorporating the PIN estimated from the data of NYSE stocks from 1983 to 1998 into a Fama and French (1992) asset-pricing framework. The model they used was simplified by assuming the uninformed are equally likely to buy and sell ($\varepsilon_b = \varepsilon_s$) and news is equally likely to be good or bad ($\delta = 0.5$). Their results showed that information does affect asset prices, with a difference of 10 percentage points in PIN resulting in a 2.5 percent difference for expected annual returns. They rationalise this finding as follows: "in a world with asymmetric information, an uninformed investor is always at a disadvantage relative to traders with better information…Holding many stocks cannot remove this effect … In this sense, asymmetric information risk is systematic because, like market risk, it cannot be diversified away".

The success of this information-based trading model supports the study's validity in this thesis.

2. 2 ASYMMETRY IN BID AND ASK PRICES

A large part of market microstructure research builds on the notion that new information that is conveyed by trades will cause revision of market quotes, where bid and ask quotes are usually modeled as the result of adding a premium and subtracting a discount to the efficient price (Glosten, 1987). The assumption that the bid and ask quotes are posted symmetrically around the efficient price is adopted by most of the models about price formation. For example, in Huang and Stoll's (1997) model, the transitory components of bid and ask prices are treated as constant and equally-sized; in Glosten and Harris's (1988) model, the dynamics of bid and ask are characterized by the same stochastic process. Besides, bid and ask quotes are sometimes assumed to respond to a shock simultaneously upward or downward, and by the same amount (e.g. Golsten and Milgrom 1985); or like Easley and O'Hara (1992), an assumption that whether a trade is buyer-initiated or seller-initiated is equally informative is used for modeling, believing that buys and sells only determine the direction, but not the magnitude of bid and ask revision.

If the assumption in the model is that the buys and sells are equally likely, the result that the premium added and the discount subtracted is symmetrical follows. So "symmetry assumption" of bid and ask, as called by Escribano and Pascual (2006), is reasonable enough in that case. However, it is not always the case that the buys and sells are equally likely. For example, on a day where analysts make a "buy" recommendation, more buy orders than sell orders may be expected. To neutralize the expected profit, market makers are quite likely to give a different premium and discount, because a small premium and large trading will balance a large discount and small trading.

This "symmetry assumption" has been challenged in several studies. Kavajecz (1999) argued that to make themselves immune to adverse selection cost, the specialists' quotes reflect the interest on the limit order book, and only on the side (or sides) of the limit order book where they believe there is a chance of informed trading. That is to say, the specialist is selectively providing liquidity and selectively protecting himself from the market. Hasbrouck (1999) pointed out the assumption that the quote exposure cost is the same on both the bid and ask sides is reasonable only if the same quote-setter is active on both sides of the market, and the quotes are not sensitive to current inventory positions. However, in most stock exchanges, as is the case of the NYSE, quotes reflect the interests of several traders. Since different agents may be subject to different trading costs and different individual limit order traders, the offer and demand components of the spread may vary asymmetrically about the efficient price. He captured this by a model suggesting that bid and ask quotes arise from two independent processes: an implicit efficient price and quote exposure (market making) costs. Both components are continuous random variables where the implicit efficient price follows ARCH dynamics and the quote exposure costs are autoregressive. The filtered maximum likelihood estimation of the model showed that while both bid and ask quotes drop and the spread widens, the quote-exposure cost on the bid and ask sides change asymmetrically. The bulk of spread increase attributes to the bid-side. That is, the implicit efficient price does not track the midpoint of the bid and ask quotes. Instead it lies above the quote midpoint after the drop, which means that the rounding transformation generating the discrete bid and ask quotes is asymmetric.

Biais et al. (1995) shows that asymmetries between bid and ask quotes are not exclusive of the NYSE. The Paris Bourse, a pure order-driven market, also shows an asymmetric bid-ask adjustment. These authors conclude that “there is additional information in analyzing the dynamics of bid and ask prices jointly rather than averaging them through the quote midpoint”.

The asymmetry has another aspect: the price impact of a buyer-initiated trade is not equivalent to that of seller-initiated trade. Holthausen et al. (1987) documented the effects of large (block) transactions on the prices of common stocks traded on the New York Stock Exchange. The results suggested that for seller-initiated transactions, price effects are predominantly temporary, however for buyer-initiated transactions, price effects are permanent. They hypothesize that large sales are less likely to contain information because they are more likely to be liquidity motivated. Koski and Michaely (2000) showed that price and liquidity effects are significantly associated with information content and timing of trades, but the results are stronger for purchases than sales. Lakonishok and Lee (2001), when examining insider trading activities, showed that insiders are able to predict market movements better. However, the information content of insiders' activities comes from purchases, while insider selling appears to have no predictive ability. This documented asymmetry that buyer-initiated trades are usually found to be more informative than seller-initiated trades is consistent with the practice of restrictions on short selling, confirming that those restrictions prevent insiders from exploiting negative information. Besides, it also helps the explanation that the choice of selling a particular stock out of the numerous possibilities conveys more favourable information than selling one stock from a particular individual-held portfolio.

Escribano and Pascual (2006) extended the vector autoregressive (VAR) model introduced by Hasbrouck (1991) and jointly model the trading process and the revisions of market quotes. Hasbrouck builds on a "weak symmetry assumption" that the quote midpoint must revert to the efficient price as the end of trading approaches and concluded that the bid and ask prices may not be symmetrically posted around the efficient price, however, the expected impact of a buyer-initiated shock is exactly reverse of a seller-initiated shock. Escribano and Pascual (2006) generalised the bivariate VAR model by a vector error correction (VEC) model with four dependent variables: changes in the ask price, changes in the bid price; buyer-initiated trades, and seller-initiated trades. Using the NYSE samples, they reported that bid and ask quotes do not respond symmetrically after trade-related shocks: they tend to be revised in the same direction, but not by the same amount; and average long-term impact of a buyer-initiated trade on the ask quote is larger than the average long-term impact of a similar seller-initiated trade on the bid quote, supporting the idea that buyer-initiated trades are more informative than seller-initiated trades.

2.3 INFORMED AND UNINFORMED TRADERS

Market microstructure theory is characterised by the co-existence of both the informed and the uninformed trader. This observation is credited to Bagehot (1971), who noted that there is a distinction in the market between market gains and trading gains, and that trading losses encountered by average investors arise because of the presence of some traders who have superior information. Copeland and Galai (1983) formalized the concept of information costs by their model, which was extended by Glosten and Milgrom (1985) and others. Here in this paper, as usual, informed traders refer to those traders who know more about the future movement of prices than other traders. For example, an officer of a corporation or others who have access to private information about the corporation.[7]

2.3.1 FINANCIAL ANALYSTS AND INFORMED TRADERS

Financial analysts have been employed as a direct proxy for informed traders in a number of studies. In Glosten and Milgrom (1985), individuals who are particularly skilful in processing public information (financial analysts) are regarded as informed traders. There are more examples in empirical studies: Skinner (1990) used analyst following as a proxy for the level of private information being produced. Brennan et al. (1993) regarded the number of analysts as a proxy for the number of informed investors in their empirical study on the prediction from Holden and Subrahmanyam (1992) that as the number of informed investors increases, the share price will reflect new information more rapidly. Chung et al. (1995) suggested using the number of financial analysts as a proxy for information asymmetry and supported the notion that specialists and financial analysts make their decisions interactively: Specialists establish the bid-ask spread of a stock according to the extent of information asymmetry (the number of financial analysts following the stock) and more financial analysts will follow stocks with a greater spread.

However, Brennan and Subrahmanyam (1995) investigated the allegation that if financial analysts are informed traders, then one might expect to find greater adverse selection costs for the stocks with more financial analysts, corresponding to the increased risk that market makers face in trading with the informed. However, measuring the adverse selection costs by the λ given by Kyle (1985), they find the opposite: firms with many analysts face a smaller adverse selection cost than do firms with fewer analysts.

[7] This private information usually takes the form of signals about the firm's project cash flows.

This is interpreted by Easley et al. (1998) to be "consistent with the notion that financial analysts are uninformed, or even misinformed, traders". Further they used a trade-based empirical technique to estimate the probability of information-based trading for a sample of NYSE stocks that differ in analyst coverage, and found that the number of analysts is negatively related to the probability of information-based trading and the probability of private information events is the same for stocks with high or low analyst following. What they conclude is that financial analysts do not appear to create private information and they are not a good positive proxy for information-based trading. This is consistent with the idea that analyst recommendations are generally based on public information rather than private information, supported by the findings of Womack (1996) that only 24 of 694 recommendations in the sample used private or new fact in their discussion.

Besides, the situation for accessing private information has changed a lot for financial analysts since October 23, 2000, the day the Securities and Exchange Commission (SEC) implemented Regulation Fair Disclosure. Reg FD prohibits selective disclosure of material information about the companies to analysts and other investment professionals. Under the regulation, any intentional disclosure of material non-public information by firms to analysts or other parties must be simultaneously released to the general public. Unintentional disclosures must be disclosed publicly within 24 hours. This means that the financial analysts would have no better information than that available to all investors. Empirical support from Gintschel and Markov (2004) showed that in the post-Regulation FD period, the absolute price impact of information disseminated by financial analysts is lower by 28% than in the pre-Reg FD period, confirming the goal of Reg FD to curtail the flow of private information to financial analysts.

As the information available to financial analysts may differ from that of informed insiders, doubt from investors and specialists about their stock recommendation accuracy seems totally natural and inevitable.

2.3.2 MARKET MAKER AND INFORMED TRADER

In those information models, an implicit assumption is that the market maker is uninformed. Remember that in a Bayesian learning model, the market maker does not know what the "true" value of the asset is, and thus is the same as other uninformed traders in this respect. Madhavan and Panchapagesan (2000) supported the reasonableness of this assumption with two pieces of evidence. One is that if market makers do have superior information, the relationship between changes in market maker inventory levels and subsequent price rises should be positive; however a negative relationship was found in studies of the NYSE and OTC markets. The other comes from studies showing that market maker purchases tend to be followed by declines in the ask prices while sales are followed by increases in bid prices, which is the opposite of what one would expect if market makers were informed. So the assumption that the market maker is uninformed seems valid.

2.4 INFORMATION CONTENT OF ANALYST RECOMMENDATIONS

Although analyst recommendations are not based on private information, they do provide information to the market. Womack (1996) concluded that the recommendations embody valuable information, even though few recommendations coincide with new public news or provide previously unavailable facts (only 24 of 694 recommendations in the sample used private or new fact in their discussion). Using data from *First Call*, the author found significant initial price and volume reactions to recommendation changes (added-to-buy, removed-from-buy, added-to-sell and removed-from-sell), both at the three-day event window and in months before and after the event. On average, size-adjusted prices increase 3.0 percent for buy recommendations and drop 4.7 percent for sell recommendations. There is also significant post-recommendation drift associated with buy recommendations with an incremental mean size-adjusted return of +2.4 percent for the first post-event month beginning two days after the recorded date of the recommendation. Sell recommendations are associated with post-recommendation drift of –9.1 percent over a longer six-month post-event period. Before the removal of buy and sell recommendations, excess returns are in a direction consistent with the recommendations that were in place before the recommendation removal. Hence Womack (1996) concludes that analysts have market timing and stock picking abilities.

This finding about abnormal returns for recommendation change events is consistent with the previous literature. Elton et al. (1986) showed that excess returns are found in the month during which there is a change in the brokerage firm recommendations, as well as during the next two months. An approximate 4.5% extra return can be earned by purchasing new buys rather than new sells. Stickel (1995) found an extra return of +1.16 percent and –1.28 percent for an 11-day event window.

Individual recommendations such as the Value Line Investment Survey or the "Dartboard" column[8] published by the *Wall Street Journal* have documented similar re-

[8] The "Dartboard" column is published monthly in the *Wall Street Journal*. In this column, four investment analysts recommend one stock each, called "Pros' Picks". The *Journal* compared the performance of these four stocks to the performance of four securities that are randomly selected (by the throw of a dart by *Journal* staff), the "Dartboard Stocks". On average, the stocks recommended for the "Dartboard" column are smaller in capitalization and higher in volatility than the stocks recommended by the major U.S. brokerage firms.

sults. Stickel (1985) finds abnormal event-period returns of +2.4 percent for firms added to Value Line rank 1 (the highest rank, a buy recommendation) and –0.3 percent for firms added to rank 5 (the lowest rank, a sell recommendation). Davies and Canes (1978) examined the effect on market prices of the publication of analysts' recommendations in the *Wall Street Journal* column "Heard on the Street", and documented an abnormal return of 0.923 percent on the day[9] a stock receives a favourable mention in the column and a negative return of –2.374 percent if the stock receives an unfavourable mention. Beneish (1991), although arguing against the secondary reporting of analysts' recommendations affecting stock prices as stated by Davies and Canes (1978), did confirm the significant average abnormal stock return performance, not only on the day of publication, but also on the preceding two trading days. Barber and Loeffler (1993) analyzed the price and volume effect of analysts' recommendations published in the "Dartboard" column of the *Wall Street Journal*. Average positive abnormal returns of 4 percent and doubled average normal volume levels are documented for the two days following publication of the recommendations. However the positive abnormal return is partially reversed within 25 trading days, reflecting a naïve buying pressure as well as the information content of the analysts' recommendations.

Most recently, in the examination of the market reaction to an insider trading case that involved five stockbrokers who had advance copies of a stock analysis column named "Inside Wall Street" (IWS)[10] in *Business Week* magazine the day before its public release, Fishe and Robe (2004) reported an average abnormal return of 4.75 percent one

[9] The Wall Street Journal is a morning newspaper which is available to investors prior to the opening of trading.
[10] This Business Week scheme started in June 1995 and ended with the February 5, 1996 issue.

day after the publication before the illegal inside trading period[11] and 5.38 percent cumulative abnormal return in the two days before and after the publication[12] (and 3.87 percent one day after the publication) after that period. All are statistically significant at the 99% level of confidence, giving support once again that analyst recommendations are regarded as informative by the market.

[11] That is between June 5, 1995 and January 29, 1996.

[12] The column is publicly released after the close on Thursday, leaving Friday as the day after the release and Thursday as the day before the release.

CHAPTER 3

METHODOLOGY AND DATA

This chapter is designed to explain the methodology and introduce the data used in deriving the results. Section 1 explains the model and the methodology on trade direction classification, maximum likelihood estimation, test technique and probability of information-based trading. The hypotheses are discussed as well. Section 2 describes the sample selection and data.

3.1 METHODOLOGY

Specialists are the middlemen in the market operation of exchanges like the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX). Glosten and Milgrom (1985) propose the following model for bid and ask prices set by the specialists:

$$a_t = E\left[V \middle| S_t, Z_t > a_t\right],$$

$$b_t = E\left[V \middle| S_t, Z_t < b_t\right], \tag{3.1}$$

where S_t is the information available to the specialist at time t, and $\{Z_t > a\}$ refers to the event that the investor makes a purchase and $\{Z_t < b\}$ refers to the event that the investor makes a sale.

If the true value of the stock only has two possible outcomes, either low (V_d) or high (V_u), then (3.1) can be simplified as follows,

$$a_t = E[v|B_t] = V_d \Pr\{V = V_d|B_t\} + V_u \Pr\{V = V_u|B_t\},$$

$$b_t = E[v|S_t] = V_d \Pr\{V = V_d|S_t\} + V_u \Pr\{V = V_u|S_t\}, \tag{1.1}$$

which we've discussed in Chapter 1. Because of the learning process, this sequential trading model allows the adjustment of prices to information to be analyzed on a trade-by-trade basis.

In the spirit of Glosten and Milgrom (1985), Easley and O'Hara (1992) gave a structural model based on the sequential trade tree diagram shown in Figure 1. Induced by this model, the likelihood function for a single trading day is

$$\begin{aligned} L(\theta|B,S) = (1-\alpha)e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!} + \alpha\delta e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-(\mu+\varepsilon_s)}\frac{(\mu+\varepsilon_s)^S}{S!} \\ + \alpha(1-\delta)e^{-(\mu+\varepsilon_b)}\frac{(\mu+\varepsilon_b)^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!} \end{aligned} \tag{2.1}$$

where $\theta = (\alpha, \delta, \varepsilon_b, \varepsilon_s, \mu)$ is the parameter vector. And the likelihood of observing the data $M = (B_i, S_i)_{i=1}^I$ over I trading days is just the product of the daily likelihood function,

$$L(\theta|B,S) = \prod_{i=1}^{I} L(\theta|B_i, S_i) \tag{2.2}$$

where (B_i, S_i) is trade data for day i=1,…, I.

With this model, we can work backwards from observing a particular sequence of trades to discover information about the underlying structural parameters. To facilitate calculation, maximizing (2.2) is equivalent to maximizing its log-likelihood form:

$$\ln L(\theta|B,S) = \sum_{i=1}^{I} \ln L(\theta|B_i, S_i)\,. \tag{3.2}$$

By maximizing (3.2) over θ which includes $\alpha, \delta, \varepsilon_b, \varepsilon_s, \mu$, using the data set M, we are able to determine estimates for the underlying structural parameters of the model. In fact, the model interprets the normal level of buys and sells for a stock as uninformed trade to identify ε_b and ε_s. Abnormal buy or sell volume is interpreted as information-based trade, used to identify μ. The number of days in which there is abnormal buy or sell volume is used to identify α and δ. However, the maximum likelihood actually does all of this simultaneously.

The dataset M is a group of data on the number of buy- and sell- initiated trades per day. Although how many buys and how many sells in each trading day are not available immediately from any databases, the availability of intraday trade and quote data, which can be attributed to the automation of stock markets, has opened the possibility of determining the trade direction.

3.1.1 TRADE DIRECTION CLASSIFICATION

There are three trade classification algorithms extensively used in microstructure studies, the quote rule, the tick rule, and Lee and Ready's (1991) rule (LR rule hereafter).[13]

[13] For the derivation of these approaches, see Hasbrouck (1988), Blume et al. (1989), and Lee and Ready (1991).

A. Quote Rule

The quote rule classifies a transaction as a buy if the trade price is above the midpoint of the bid and ask quote; or as a sell if the trade price is below the midpoint. Those transactions traded at the midpoint are not classified.

B. Tick Rule

The tick rule classifies a trade based on price movements relative to previous trades. If the trade price is above the previous price, then it is an uptick. If there is no price change but the previous trade is an uptick, then this trade is classified as a zero-uptick. Both upticks and zero-upticks are classified as buys.

The tick rule has been used when quote data are not available. In theory all trades can be classified as either a buy or a sell order by using a tick rule. However as Lee and Ready (1991) said: "The primary limitation of the tick rule is its relative imprecision when compared to a quote-based approach, particularly if the prevailing quote has changed or it has been a long time since the last trade."

C. Lee and Ready's (1991) Rule

LR's procedure is essentially a combination of the quote rule and tick rule. First, classify a trade according to the quote rule (above or below the midpoint), and then classify those transactions at midpoint using the tick rule. Given the reporting procedure on the NYSE, LR also suggest comparing transaction prices to quotes reported at least five seconds before the transaction was reported.

Although it is not easy to determine how well these algorithms work because of the limitation on the source of the original order, some empirical tests do provide evidence on the validity of trade classification algorithms. Using NYSE data, Odders-White

(2000) reported an agreement rate of 85% between the actual order and LR's algorithmic inference. Finucane (2000) concludes that for NYSE firms, the tick test and LR method have very similar performance accuracy. However, Ellis et al. (2000) used a NASDAQ proprietary data set that identifies trade direction and found the quote rule, the tick rule, and the LR rule correctly classify 76.4%, 77.66%, and 81.05% of the trades respectively. Based on these results, we will follow the LR rule in this paper.

3.1.2 MAXIMUM LIKELIHOOD ESTIMATION

The basic idea of maximum likelihood estimation is, as the name implies, to find a set of parameter estimates, $\theta = (\alpha, \delta, \varepsilon_b, \varepsilon_s, \mu)$ in our case, such that the likelihood of having obtained the actual observed sample is maximized. The likelihood function is the joint density of the observations (B_i, S_i). For any given $\theta = (\alpha, \delta, \varepsilon_b, \varepsilon_s, \mu)$, this function tells us how likely we were to have observed the sample $M = (B_i, S_i)_{i=1}^{I}$. Then the joint probability density for the model being estimated is evaluated at the observed values of the dependent variables (B_i, S_i) and treated as a function of the model parameters. The vector of ML estimates $\hat{\theta}$ yields the maximum of this function.

Computer software typically provides accurate values for a Poisson probability to approximately 10^{-16}. If the true probability is smaller than this, then it is assigned a value of zero. This causes difficulty in determining maximum likelihood since if one observation turns out to have a probability reported as zero, then the product must also be zero (and the logarithm must be negative infinity, which also reports as an error). On the other hand, software typically provides accurate values for a normal probability to approximately 10^{-308}. Since the computer software could not give the joint density to Poisson distribution as accurately as to normal distribution, we use the normal limit of the Poisson distribution as an approximation: For large parameter values, the Poisson distribution approaches the normal distribution, (Haight 1967). Let X_λ be a Poisson distributed variable with parameters λ, and let Y_λ be a normal random variable with mean and variance λ. Then $\Pr\{X_\lambda \le z\} \to \Pr\{Y_\lambda \le z\}$ as $\lambda \to \infty$ uniformly in z. This approximation is very accurate for large values $\lambda > 1000$, but for smaller values it is appropriate to apply a correction to account for using a continuous distribution to approximate a discrete distribution. Since $\Pr\{X_\lambda \le z\} = \Pr\{X_\lambda \le z + c\}$ for any constant $0 \le c < 1$, $\Pr\{X_\lambda \le z\} \to \Pr\{Y_\lambda \le z + c\}$ as $\lambda \to \infty$ uniformly in z. A natural choice for the constant is the midpoint $c = 0.5$. This approximation, $\Pr\{X_\lambda \le z\} \approx \Pr\{Y_\lambda \le z + 0.5\}$, is quite accurate for $\lambda > 10$,[14] and since this represents the average number of buys and sells each day, and the minimum number of trades among all of the days and stocks that we examine is 42, so the average easily meets this requirement.

Another problem with the maximum likelihood estimation is the restrictions of the parameters. Both α and δ are probabilities, so they should be restricted between 0 and 1 inclusive. And ε_b, ε_s, and μ are the arrival rates of different traders, so they should all be non-negative. We estimate increasing transformations of the parameters $e_s = \ln(\varepsilon_s)$, and $a = \tan\{\pi(\alpha + 0.5)\}$, etc. In this case the transformed parameters e_s, a, etc. are estimated without constraints, and by the invariance of maximum likelihood estimators, we can find the maximum likelihood estimates of our original parameters by applying the appropriate inverse functions.

[14] http://en.wikipedia.org/wiki/Poisson_distribution

3.1.3 HYPOTHESES AND TEST TECHNIQUE

As we discussed before, it is hard to say whether analysts genuinely contribute new information about the value of the stock being analysed, because analysts typically do not have more information than the market when making their forecasts. However they may be able to better interpret this available information due to their expertise and thus value the stock more accurately than the market. Furthermore, investors may or may not follow the analyst's advice, (i.e. they may or may not believe that the analyst is able to interpret information better than the market). This gives four possible events: (1) Analysts make accurate recommendations and investors believe them, (2) Analysts make inaccurate recommendations, but investors believe them to be accurate, (3) Analysts make accurate recommendations, but investors don't believe them, and (4) Analysts make inaccurate recommendations, and investors correctly believe these recommendations to be inaccurate.

To distinguish between these four possible events, we bring a third class of trader into consideration, which we call analyst followers, who base their trades on analysts' recommendations. Then we separate the whole test period into three sets: the dates when there is no change in analysts' recommendation (called the no-recommendation period hereafter), the dates when there is positive change in analysts' recommendation such as going from sell to hold recommendations (up-recommendation period), and the dates when there is negative change in analysts' recommendations (down-recommendation period). In the maximum likelihood estimation, we use two dummy variables to identify the three periods: one equals to 1 in the up-recommendation period and 0 otherwise, and the other equals to 1 in the down-recommendation period and 0 otherwise. Thus we estimate

$\theta = (\alpha, \delta, \varepsilon_b, \varepsilon_s, \mu)$ for each period and check whether the parameters are significantly different in different periods.

The technique we use to test the hypothesis whether there are significant changes for the parameters in different periods is the likelihood ratio test. Let θ be a vector of parameters to be estimated, and now we can specify some sort of restriction on the parameters (e.g. H_0: α in the up-recommendation period equals to α in the no-recommendation period). Let $\hat{\theta}_U$ be the maximum likelihood estimator of θ obtained without the constraints, and let $\hat{\theta}_R$ be the constrained maximum likelihood estimator. If $\hat{L}_U$ and $\hat{L}_R$ are the likelihood functions evaluated at these two estimates, then the likelihood ratio is

$$\lambda = \frac{\hat{L}_R}{\hat{L}_U}, \tag{3.3}$$

which must be between zero and one. The likelihood ratio test statistic works as follows: Under regularity and under H_0, the large sample distribution of $-2\ln\lambda$ is chi-squared, with degrees of freedom equal to the number of restrictions imposed (Greene, 2003). So if the value of $-2\ln\lambda$ exceeds the appropriate critical value from the chi-squared table, the null hypothesis (or the restriction) will be rejected, supporting the significant difference of the parameter in two different periods.

If we find a different α, which is the probability of new information, for days with recommendation changes, compared to no-recommendation days, we may conclude that financial analysts can cause the probability of private information events occurring to change by announcing their recommendation, where we define a private information event as the occurrence of a signal that is not publicly observable about the future value of the asset. If a higher α is found in up- and/or down-recommendation periods (in this case, the analyst followers shall be regarded as informed traders), it may be taken as a support that financial analysts can discover some information that otherwise would not have become private information, and make it possible for their clients to trade on this information. If a lower α is found, we may say that analysts have the capacity to accurately understand, interpret and effectively make a piece of information publicly available that would otherwise be private. Or it may be that analysts are good at predicting when information will arise and therefore choose to release recommendations more frequently on days when information events occur. In this case they don't actually affect the probability directly, but a change in α would be associated with recommendations rather than be caused by them. Since we are not sure whether or not financial analysts affect the probability of private information events, we leave it as an empirical question.

Since the probability that new information is bad news, δ, is conditioned on the occurrence of private information events, the change of α, no matter how, would make it hard for us to interpret δ independently. So we use the unconditional probability $\gamma = \alpha \times \delta$, which is the probability of a "bad-news days", and $\beta = \alpha \times (1- \delta)$, which is the probability of a "good-news days" instead.[15] If analysts have forecast ability on the occurrence of information events and can effectively time their recommendations to coincide, we may expect to see a higher probability of "good-news day" or a lower probability of "bad-news day" (both are positive pieces of information) on days when they increase their recommendations, i.e. in the up-recommendation period. In the down-recommendation period, a higher γ or a lower β also supports the accuracy of financial analysts.

While changes in the parameters α and δ are associated with accuracy of the analysts' recommendations, the other three parameters relate to trader composition which is

[15] This is consistent with the three possible events given in Figure 1.

associated with the market response to the analysts' recommendation: ε_b and ε_s are the arrival rates of uninformed sellers and buyers; μ is the arrival rate of informed traders. Changes in these parameters allow inference about how market participants respond to recommendations. We check whether the trader composition is different in recommendation and no-recommendation periods and how they differ. [As we discussed above, we can consider the analyst followers as informed traders if and only if the analysts are able to forecast information events (an increase of α, or an appropriate change in β, or γ), otherwise, the analyst followers should be regarded as uninformed traders.] That is to say, if in the up-recommendation periods, the buyers' arrival rates increase significantly, or if in the down-recommendation period, the sellers' arrival rates increase, then we can draw the conclusion that investors typically believe analysts, i.e. Events (1) and (2). On the other hand, if in the up-recommendation period, buyer's arrival rates do not change at all or even decrease, and similarly for sellers in the down-recommendation period, then this supports Events (3) and (4) where investors do not believe analysts. They may even act against the analysts' recommendation. It could be that an asymmetric response between up- and down-recommendation periods is observed. This may support credibility of one form of recommendation change over the other.

As to the arrival rate of informed traders, μ, we would take its change as the response of existing informed traders to the analyst's recommendation except the case when μ increases with the increase of α, which as we discussed above, shows that the analysts find out some private information so that their clients become "informed" traders. Since the informed traders could believe that analysts have worse information than they have, it is possible that they will trade more just to exploit opportunities.

3.1.4 PROBABILITY OF INFORMATION-BASED TRADING

As we discussed above, specialists try to solve the adverse selection problem by giving rise to the bid-ask spread and they update the bid-ask spread according to their assessment of the probability of information-based trading. Since it is possible that on those days when analysts announce their recommendations, the specialists might suspect that orders in the opposite direction of the analyst's recommendation may be more likely to be made by informed traders, thus giving different conditional probabilities of informed trading in different situations. For example on days with up-recommendation changes, they may give a higher probability of information-based trading to a sell order compared to a buy order. If that's the case, we may expect to see asymmetry between bid discounts and ask premiums.

If the specialists do value the "lemons discount" and "peach premium" in an asymmetrical way, the midpoint price we observe from the market would not be the full-information price. For example, they may give a larger discount for the bid price and a smaller premium for the ask price when the recommendation from financial analysts is "buy", leading to a midpoint price that is lower than the full-information price (expected value of the stock). This would also be interpreted by the market as over optimism by financial analysts, even though the analysts are accurate.

Based on the unconditional probability of information-based trading (PIN) given by Easley et al. (1998),[16] we work out the conditional probabilities, namely PIN|sell and

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[16] We uncovered a small error in the PIN formula given by Easley et al. (1998), $PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_b + \varepsilon_s}$. Since conditioned on the occurrence of an information event, the probability that the waiting time for the

PIN|buy. Since in the model, all traders are supposed to arrive independently of each other and according to Poisson processes, the waiting times for the next uninformed buyer, uninformed seller and informed trader are independent and exponentially distributed with rates ε_b, ε_s, μ respectively. This implies that the minimum waiting time for any uninformed trader is exponentially distributed with rate $\varepsilon_b + \varepsilon_s$. Conditioned on the occurrence of an information event, the probability that the waiting time for the informed traders is less than the minimum waiting time for an uninformed trader is $\frac{\mu}{\mu + \varepsilon_b + \varepsilon_s}$. Since if an information event has not occurred, informed traders will not trade, this conditional probability is zero. Thus the unconditional probability that the next trader is informed is

$$
\begin{aligned}
PIN &= \Pr\{X_\mu < \min\{X_b, X_x\} | \text{information event}\} \times \Pr\{\text{Information event}\} + 0 \\
&= \frac{\alpha\mu}{\varepsilon_b + \varepsilon_s + \mu} \qquad (3.7)
\end{aligned}
$$

where X_b, X_s and X_μ represent the waiting times for next uninformed buyer, uninformed seller and informed trader respectively, and the probability of information event occurring is α.

Based on the observation that informed traders only sell if they have seen bad news, the probability of information-based trading conditioned on a sell (PIN|sell) would be $\Pr\{X_\mu < \min\{X_b, X_s\} | sell\}$ and equal to $\frac{\alpha\delta\mu}{\mu + \varepsilon_s}$. The derivation is as follows:

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informed traders is less than the minimum waiting time for an uninformed trader is $\frac{\mu}{\mu + \varepsilon_b + \varepsilon_s}$, and the probability of the occurrence of an information event is α, the unconditional probability that the next trader is informed is $PIN = \frac{\alpha\mu}{\mu + \varepsilon_b + \varepsilon_s}$.

$$\Pr\{X_\mu < \min\{X_b, X_s\} | sell\}$$

$$= \Pr\{X_\mu < \min\{X_b, X_s\} | sell\ \ and\ \ bad\ \ news\} \times \Pr\{bad\ \ news\}$$

$$= \Pr\{X_\mu < \min\{X_b, X_s\} | \min\{X_\mu, X_s\} < X_b\ \ and\ \ bad\ \ news\} \times \Pr\{bad\ \ news\}$$

$$= \frac{\Pr\{X_\mu < \min\{X_b, X_s\} and\ \ \min\{X_\mu, X_s\} < X_b | bad\ \ news\}}{\Pr\{\min\{X_\mu, X_s\} < X_b | bad\ \ news\}} \times \Pr\{bad\ \ news\}$$

$$= \frac{\Pr\{X_\mu < \min\{X_b, X_s\} | bad\ \ news\}}{1 - \Pr\{X_b < \min\{X_\mu, X_s\} | bad\ \ news\}} \times \Pr\{bad\ \ news\}$$

$$= \frac{\left(\dfrac{\mu}{\mu + \varepsilon_s + \varepsilon_b}\right)}{\left(1 - \dfrac{\varepsilon_b}{\mu + \varepsilon_s + \varepsilon_b}\right)} \alpha\delta$$

$$= \frac{\alpha\delta\mu}{\mu + \varepsilon_s}$$

Similarly, the probability of information-based trading conditioned on a buy is $PIN \mid buy = \dfrac{\alpha(1-\delta)\mu}{\mu + \varepsilon_b}$.

Our hypothesis about the information-based trading is: if the analysts' recommendations are associated with information events, we would see a high PIN in recommendation periods; if specialists know that uninformed investors on average believe analysts, on recommendation days there would be an increase of trading in the direction of the recommendation, and orders in the opposite direction of recommendation are more likely to be an information-based trade (given that specialists believe the analysts have no private information so the analyst followers are still "uninformed"), they would give a higher

PIN|sell and a lower PIN|buy in the up-recommendation period, and lower PIN|sell and higher PIN|buy in the down-recommendation period.

From a modeling perspective, we adjust the basic model by considering a separate game tree (i.e. Figure 1) applied for each sub-period we consider. This causes our trader arrival processes to be conditionally independent Poisson, and the parameters to be conditional probabilities and means, conditioned on the type of recommendation change. Therefore, if any of these parameters are affected systematically by analyst recommendation changes (as some of them are), this doesn't compromise the independence required for estimation or for calculating PIN, etc.

3.2 SAMPLE SELECTION AND THE DATA

This study spans a two-year period from January 1, 2001 to December 31, 2002. The two databases used are IBES and TAQ2.

IBES, the Institutional Brokers Estimate System, gathers and compiles the different earnings estimates of over 18,000 companies in 60 countries. More than 850 firms contribute data to I/B/E/S, from the largest global houses to regional and local brokers, with US data back to 1976 and international data back to 1987. The IBES is a quality source for analysts' forecast data, research reports, tools, and applied intelligence, whereby investors and researchers are able to examine the different analyst estimates for any given stock without necessarily searching for each individual analyst. As William Sharpe, Nobel Laureate says in his classic text *Investments,* "While I/B/E/S is not the only company collecting earnings expectations data...it was the first and remains the leader in the field."

For sample selection, all recommendations for the U.S. listed stocks are retrieved for two years from January 2001 to December 2002, giving 78,424 non-missing observations in total with five consensus recommendation categories from 1 to 5 representing strong buy, buy, hold, sell and strong sell respectively. Following previous research, only the days with changes in recommendations will be regarded as event days. If the average recommendation is less than the average in the previous day, then we consider it an up-recommendation to the market on that day; if the average recommendation is greater than the previous day average, then we treat it as a down-recommendation to the market on that day. Thus we figure out the information event days of each firm. The top thirty firms listed in NYSE and AMEX (since we focus on the specialist market) with the most information event days go into our sample. The list of the thirty firms is given in Table 1. They cover 15 different industry classification codes and the total assets at the end of year 2002 vary from 2,548 million dollars to 167,468 million dollars.

The ticker data are retrieved from the Trade and Quote (TAQ) database. The TAQ2 database contains intraday transactions data (trades and quotes) for all securities listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), NASDAQ, and National Market System (NMS) since 1993. Based on the ticker data, we classified the trades into buy and sell using the LR algorithm, thus transforming them into daily numbers of buys and sells. Then we divided the whole data of each firm into three groups: no-recommendation period, up-recommendation period and down-recommendation period. While doing this, one problem we encounter is that some of the analysts' recommendations came to the market on non-business days. In that case, if there is no other information coming to the market around that day, then the following business days are treated as the event day. If there are conflicting information events around that day, then we ignore both days from both the non-information period and the information period. We do this because we can not classify the information set and we try to avoid the unnecessary noise. This may lead to one or two less observation in these three groups than in the whole group.

Table 2 provides the statistics of the daily numbers of buys and sells. Panel A reports the summary statistics across the thirty firms and Panel B reports the details for each firm in different periods. For the two-year period, there are 494 observations in total. The mean of daily buys over the two-year period for each firm ranges from 274 to 1589, and the mean of daily sells for each firm ranges from 213 to 1477. This results in the mean of daily trades (the sum of buys and sells) ranging from 487 to 3065, which shows great diversity although all thirty firms are relatively actively traded. In the up-recommendation period, we have 21 to 36 observations (days), 20 to 38 observations in the down-recommendation period, and 419 to 451 observations in the no-recommendation period. In the no-recommendation period, the mean of daily buys across the thirty firms range from 267 to 1581; in the up-recommendation period, the means range from 343 to 1681; in the down-recommendation period, the means range from 330 to 1716. The mean of daily sells range from 208 to 1474 in the no-recommendation period, from 273 to 1569 in the up-recommendation period and from 249-1502 in the down-recommendation period. As we can see, the average number of trades (both buys and sells) is generally greater in either recommendation period than in the no-recommendation period. This suggests that the market as a whole does respond to analysts' recommendations in some way.

Table 1

The list of firms

Ticker	Name of Company	Industry	NAICS[1]	Total Asset[2] (million $)
AOL/TWX[3]	TIME WARNER INC	MOTION PIC, VIDEOTAPE PRODTN	512110	115,450
APC	ANADARKO PETROLEUM CORP	CRUDE PETROLEUM & NATURAL GS	211111	18,248
AT	ALLTEL CORP	RADIOTELEPHONE COMMUNICATION	517212	16,389
AWE	AT&T WIRELESS SERVICES INC	RADIOTELEPHONE COMMUNICATION	517212	45,806
BP	BP PLC -ADR	PETROLEUM REFINING	324110	159,125
BR	BURLINGTON RESOURCES INC	CRUDE PETROLEUM & NATURAL GS	211111	10,645
BSX	BOSTON SCIENTIFIC CORP	SURGICAL,MED INSTR,APPARATUS	339112	4,450
CC	CIRCUIT CITY STORES INC	RADIO,TV,CONS ELECTR STORES	443112	3,799
COF	CAPITAL ONE FINANCIAL CORP	PERSONAL CREDIT INSTITUTIONS	522210	37,382
DNA	GENENTECH INC	PHARMACEUTICAL PREPARATIONS	325412	6,777
DVN	DEVON ENERGY CORP	CRUDE PETROLEUM & NATURAL GS	211111	16,225
EDS	ELECTRONIC DATA SYSTEMS CORP	CMP PROGRAMMING,DATA PROC-ESS	541513	18,880
EOG	EOG RESOURCES INC	CRUDE PETROLEUM & NATURAL GS	211111	3,814
GDT	GUIDANT CORP	SURGICAL,MED INSTR,APPARATUS	339112	3,716
GPS	GAP INC	FAMILY CLOTHING STORES	448140	9,902
JBL	JABIL CIRCUIT INC	PRINTED CIRCUIT BOARDS	334412	2,548
LU	LUCENT TECHNOLOGIES INC	CMP INTEGRATED SYS DESIGN	541512	17,791
MOT	MOTOROLA INC	RADIO,TV BROADCAST, COMM EQ	334220	31,152
MRK	MERCK & CO	PHARMACEUTICAL PREPARATIONS	325412	47,561

Table 1 (Cont'd)

The list of firms

Ticker	Name of Company	Industry	Industry Classification Code	Total Asset* (million $)
NOK	NOKIA CORP -ADR	RADIO,TV BROADCAST, COMM EQ	334220	24,458
PCS	SPRINT PCS GROUP	RADIOTELEPHONE COMMUNICATION	517212	23,022
Q	QWEST COMMUNICATION INTL INC	PHONE COMM EX RADIOTELEPHONE	517110	29,345
RD	ROYAL DUTCH PETROLEUM -ADR	PETROLEUM REFINING	324110	91,615
RIG	TRANSOCEAN INC	DRILLING OIL AND GAS WELLS	213111	12,665
SAP	SAP AG -ADR	PREPACKAGED SOFTWARE	511210	5,882
SBC	SBC COMMUNICATIONS INC	PHONE COMM EX RADIOTELEPHONE	517110	95,057
SGP	SCHERING-PLOUGH	PHARMACEUTICAL PREPARATIONS	325412	14,136
SLR	SOLECTRON CORP	PRINTED CIRCUIT BOARDS	334412	11,014
T	AT&T CORP	PHONE COMM EX RADIOTELEPHONE	517110	55,272
VZ	VERIZON COMMUNICATIONS INC	PHONE COMM EX RADIOTELEPHONE	517110	167,468

1 North American Industry Classification System.

2 At the end of year 2002.

3 The ticker now changed from AOL to TWX. In the following tables, we either use AOL/TWX or use AOL', according to the situation.

Table 2

Summary statistics for the daily numbers of buys and sells

Panel A: Summary across thirty firms			
	Number of Observa-tion	**Mean of Buys**	**Mean of Sells**
Total	494	274-1589	213-1477
no-recommendation period	419-451	267-1581	208-1474
up-recommendation period	21-36	343-1681	273-1569
down-recommendation period	20-38	330-1716	249-1502

Panel B: Details for each firm

Ticker	**Period**	**Number of Observation**	**Buy**			**Sell**		
			min	**max**	**mean**	**min**	**max**	**mean**
AOL'		494	607	2575	1589	482	2337	1477
	No Recommendation	438	607	2575	1581	482	2337	1474
	Up Recommendation	26	979	2354	1624	745	1978	1492
	Down Recommendation	29	951	2386	1658	636	2041	1492
APC		494	315	1795	1002	205	1687	803
	No Recommendation	446	315	1679	996	242	1687	798
	Up Recommendation	25	705	1319	1039	617	1208	844
	Down Recommendation	22	484	1795	1076	494	1101	865
AT		494	157	1343	582	98	1143	499
	No Recommendation	446	157	1343	575	98	1106	491
	Up Recommendation	24	302	987	626	235	963	537
	Down Recommendation	22	276	1223	675	241	1143	601
AWE		494	233	1751	879	158	1892	894
	No Recommendation	433	233	1660	866	158	1892	875
	Up Recommendation	30	358	1637	990	261	1539	1038
	Down Recommendation	31	346	1751	957	350	1655	1022
BP		494	203	1218	570	209	1015	493
	No Recommendation	449	203	1218	567	209	1015	492
	Up Recommendation	21	334	1164	586	270	927	501
	Down Recommendation	22	289	1003	600	216	954	505
BR		494	186	1393	653	153	1211	520
	No Recommendation	440	186	1393	648	153	1211	520
	Up Recommendation	27	319	1185	686	324	1112	513
	Down Recommendation	24	264	1235	704	226	893	536
BSX		494	87	1354	569	114	1488	479
	No Recommendation	443	87	1254	556	114	1196	472
	Up Recommendation	24	257	1354	680	230	1488	583
	Down Recommendation	26	255	1333	672	178	981	509

Table 2 (cont'd)

Summary statistics for the daily numbers of buys and sells

Ticker	Period	Number of Observation	Buy			Sell		
			min	max	mean	min	max	mean
CC		494	158	1834	606	95	1452	480
	No Recommendation	449	158	1428	587	95	1333	465
	Up Recommendation	21	264	1834	827	190	1097	625
	Down Recommendation	22	185	1740	737	226	1452	630
COF		494	298	2318	1122	234	1992	879
	No Recommendation	448	298	2318	1093	234	1789	859
	Up Recommendation	24	536	2159	1358	458	1992	1078
	Down Recommendation	20	551	2024	1416	435	1600	1079
DNA		494	230	1640	706	154	1356	545
	No Recommendation	445	321	1421	691	177	1087	537
	Up Recommendation	22	550	1640	895	400	1356	651
	Down Recommendation	25	230	1555	804	154	852	588
DVN		494	184	1116	495	127	741	370
	No Recommendation	437	184	1116	490	127	741	366
	Up Recommendation	30	203	873	508	127	563	368
	Down Recommendation	27	238	770	559	181	718	437
EDS		494	260	1612	738	288	1424	637
	No Recommendation	440	260	1612	721	288	1424	626
	Up Recommendation	26	389	1496	905	409	1317	738
	Down Recommendation	28	426	1390	851	407	1306	723
EOG		494	147	1095	523	133	978	408
	No Recommendation	443	147	1095	515	133	978	400
	Up Recommendation	23	277	1012	547	228	724	453
	Down Recommendation	27	255	942	628	289	756	495
GDT		494	256	1915	736	193	1644	638
	No Recommendation	436	256	1430	726	193	1379	629
	Up Recommendation	26	363	1915	809	344	1644	682
	Down Recommendation	31	309	1399	814	344	1076	728
GPS		494	361	1992	839	236	1379	675
	No Recommendation	432	361	1530	822	236	1379	663
	Up Recommendation	32	522	1432	928	428	1133	734
	Down Recommendation	30	491	1992	998	463	1356	784
JBL		494	295	1426	796	151	1364	631
	No Recommendation	448	295	1426	795	151	1364	628
	Up Recommendation	24	450	1279	813	402	980	675
	Down Recommendation	22	510	1172	799	394	954	637

Table 2 (cont'd)

Summary statistics for the daily numbers of buys and sells

Ticker	Period	Number of Observation	Buy			Sell		
			min	max	mean	min	max	mean
LU		494	417	2732	1269	553	2724	1331
	No Recommendation	442	417	2732	1261	553	2724	1334
	Up Recommendation	28	673	2376	1362	709	1896	1295
	Down Recommendation	24	626	1978	1300	749	1948	1316
MOT		494	438	2011	1299	435	1946	1221
	No Recommendation	447	438	2011	1292	435	1946	1211
	Up Recommendation	22	724	1771	1355	872	1553	1337
	Down Recommendation	25	1062	1769	1386	999	1794	1290
MRK		494	436	2448	1229	370	2719	1134
	No Recommendation	448	436	2230	1208	370	2719	1116
	Up Recommendation	23	858	2448	1448	778	2173	1332
	Down Recommendation	23	874	2237	1417	773	2153	1276
NOK		494	411	2069	1235	529	1834	1155
	No Recommendation	433	465	2069	1231	529	1834	1155
	Up Recommendation	32	944	1763	1283	852	1711	1173
	Down Recommendation	29	411	1569	1244	547	1656	1149
PCS		494	339	1834	859	284	1442	721
	No Recommendation	425	339	1632	836	284	1442	705
	Up Recommendation	35	555	1834	977	480	1345	808
	Down Recommendation	33	558	1709	1024	524	1409	831
Q		494	289	1875	943	416	1690	918
	No Recommendation	419	289	1725	919	416	1690	902
	Up Recommendation	36	663	1846	1099	525	1579	995
	Down Recommendation	38	534	1875	1057	468	1506	1007
RD		494	358	2141	966	311	1946	857
	No Recommendation	450	358	2141	955	311	1879	847
	Up Recommendation	22	597	2002	1072	485	1946	957
	Down Recommendation	21	538	1687	1090	536	1613	956
RIG		494	390	1878	1064	145	1601	866
	No Recommendation	444	390	1878	1053	145	1601	855
	Up Recommendation	25	680	1603	1172	471	1333	922
	Down Recommendation	24	500	1656	1156	468	1581	1000
SAP		494	42	904	274	54	606	213
	No Recommendation	446	42	904	267	54	552	208
	Up Recommendation	22	164	711	343	131	606	273
	Down Recommendation	25	143	611	330	132	460	249

Table 2 (cont'd)

Summary statistics for the daily numbers of buys and sells

Ticker	Period	Number of Observation	Buy			Sell		
			min	max	mean	min	max	mean
SBC		494	522	2450	1405	542	2413	1364
	No Recommendation	441	522	2450	1392	542	2413	1359
	Up Recommendation	27	741	2373	1526	842	2209	1409
	Down Recommendation	26	1115	2411	1502	914	2238	1416
SGP		494	463	2288	1012	390	1911	907
	No Recommendation	449	463	2288	1005	390	1911	898
	Up Recommendation	21	712	1890	1146	524	1759	1012
	Down Recommendation	24	599	2085	1036	751	1707	981
SLR		494	367	1630	864	268	1375	748
	No Recommendation	451	367	1630	862	268	1343	746
	Up Recommendation	21	505	1504	890	487	1375	751
	Down Recommendation	22	493	1271	864	504	1205	786
T		494	388	1899	1012	441	1844	1090
	No Recommendation	445	401	1899	1008	441	1844	1086
	Up Recommendation	25	388	1432	1024	644	1629	1088
	Down Recommendation	24	755	1637	1065	832	1545	1170
VZ		494	462	2717	1463	414	2243	1302
	No Recommendation	448	462	2689	1439	414	2243	1279
	Up Recommendation	21	1095	2447	1681	801	2238	1569
	Down Recommendation	25	978	2717	1716	982	2122	1502

CHAPTER 4

ANALYSES OF THE EMPIRICAL FINDINGS

This chapter presents the empirical findings of this study. Section 1 examines whether the parameters in the likelihood function (3.2), namely the probability of an information event (α), the probability of a bad news or low signal (δ), the arrival rate of uninformed buy orders (ε_b), the arrival rate of uninformed sell orders (ε_s), and the arrival rate of informed traders (μ), have significant differences in the different recommendation periods. Section 2 presents the findings about the probabilities of information-based trading, both unconditional and conditional. Section 3 reports the results of the robustness test. And Section 4 discusses the possible determinant factors of the probability of information-based trading.

4.1 TESTS ON THE CHANGE OF THE PARAMETERS

Based on the data set of daily buys and sells, we estimate the parameters α, δ, ε_b, ε_s and μ of each firm in each of the three periods, using the maximum likelihood technique. The descriptive summary of the estimated parameters across the thirty firms are given in Table 3. To test the hypotheses about whether there are significant changes for the parameter estimates in recommendation periods compared to the no-recommendation period, the technique used is the of likelihood ratio test. The results of each parameter are discussed respectively in Tables 4 to 11 (with Table 6 showing the descriptive summary of gamma and beta). The significance and the direction of the changes of each parameter in different recommendation periods are summarized in Table 12.

Table 3

Descriptive summary of the estimated parameters across the thirty firms

		Estimate in the no-recommendation period	Estimate in the up-recommendation period	Estimate in the down-recommendation period
alpha (α)	minimum	0.2925	0.1818	0.1667
	maximum	0.7252	0.8333	0.8387
	mean	0.4240	0.4397 (0.4863)	0.4503 (0.1138)
	Standard Deviation	0.0865	0.1506 (0.0039)**	0.1355 (0.0184)*
delta (δ)	minimum	0.0000	0.0000	0.0000
	maximum	1.0000	1.0000	1.0000
	mean	0.2824	0.3706 (0.1667)	0.2546 (0.6259)
	Standard Deviation	0.2392	0.3867 (0.0118)*	0.3103 (0.1672)
epsilon buy (ε_b)	minimum	221.8934	218.1051	315.6611
	maximum	1458.6111	1608.6395	1653.9981
	mean	795.8510	904.2720 (0.0000)**	863.4730 (0.0019)**
	Standard Deviation	310.7134	355.9412 (0.4688)	338.9268 (0.6428)
epsilon sell (ε_s)	minimum	214.0170	297.9744	215.4166
	maximum	1402.2740	1524.7733	1493.1513
	mean	767.1952	814.9952 (0.0171)*	852.7668 (0.0000)**
	Standard Deviation	320.2864	315.3039 (0.9333)	338.0131 (0.7737)
mu (μ)	minimum	201.3435	222.7558	185.2666
	maximum	707.9679	770.1857	784.1525
	mean	399.1360	473.4884 (0.0002)**	459.0733 (0.0027)**
	Standard Deviation	136.2552	150.2908 (0.6010)	149.7882 (0.6134)

* means significant at 5% and ** means significant at 1%.

4.1.1 ALPHA (α)

Table 3 describes the summary of the estimates of each parameter across the thirty firms, with the *p*-value of *t*-tests and *F*-tests given in parentheses under the mean and variance respectively. We can see that in both recommendation periods, the range of alpha and the variance of alpha are greater than in the no-recommendation period (the *F*-test on the difference of variance between no-recommendation and up- or down-recommendation periods gives $p = 0.0039$ and $p = 0.0184$ respectively, as shown in parentheses under the variance). However, the mean of alpha does not change significantly (with $p = 0.4863$ for the up-recommendation period and $p = 0.1138$ for the down-recommendation period respectively). Since α increases more on average in the down-recommendation period than the up-recommendation period, this suggests that there is weak evidence that down-recommendations are more credible or accurate than up-recommendations.

As shown in Table 4, the change of alpha, the probability of a private information event, is quite noisy: Among up-recommendation events, there are 16 positive changes meaning a higher probability of an information event, and 14 negative changes. And the change in alpha varies from –0.2273 to 0.2646. However, when we use the likelihood ratio test to check the statistical significance of the change, only three are significant. In the down-recommendation period, the situation is quite similar. There are 17 positive changes and 13 negative changes. And the change ranges from –0.2077 to 0.1471. But only one of the thirty firms has a significant change in the estimate of alpha. Based on the general insignificance in the change of the estimates of α, we conclude that financial analysts do not create new private information through studying public information, since otherwise it would be possible for their clients to trade on this information and we would expect to see an increased α. Furthermore, they also do not possess any direct private information, since otherwise their public announcement of this private information would make it widely available (i.e. public), so the probability of private information α would decrease.

This result turns out to be consistent with previous findings: Easley et al. (1998) showed that the probability of private information events is the same across stocks with many and few analysts, and Womack (1996) suggested that analysts' recommendations are generally based on public, rather than private, information. This also supports the general claim that the financial market is at least semi-strong efficient, and able to interpret the public information thoroughly. The expertise of professionals can do no better than the market. Our finding also gives support to the effectiveness of Regulation Fair Disclosure, which prohibits the selective disclosure of material information of the companies to financial analysts.

Table 4

Analysis of alpha (α)

Ticker	no recommendation	up recommendation				down recommendation			
	estimate	estimate	change			estimate	change		
AOL'	0.5146	0.7307	0.2162	*	+	0.5172	0.0026		+
APC	0.5155	0.5703	0.0548		+	0.5000	–0.0155		–
AT	0.4021	0.6667	0.2646	*	+	0.5455	0.1433		+
AWE	0.7252	0.8333	0.1082		+	0.8387	0.1135		+
BP	0.4432	0.3810	–0.0623		–	0.5454	0.1022		
BR	0.3380	0.2958	–0.0422		–	0.4169	0.0789		+
BSX	0.4773	0.2500	–0.2273	*	–	0.4615	–0.0158		–
CC	0.4720	0.5714	0.0995		+	0.6190	0.1471		+
COF	0.5173	0.4167	–0.1006		–	0.5500	0.0327		+
DNA	0.3265	0.1818	–0.1447		–	0.2800	–0.0466		–
DVN	0.4284	0.4000	–0.0284		–	0.5116	0.0831		+
EDS	0.3039	0.3462	0.0423		+	0.2857	–0.0181		–
EOG	0.3934	0.4783	0.0848		+	0.5323	0.1389		+
GDT	0.4627	0.4800	0.0173		+	0.3548	–0.1078		–
GPS	0.3833	0.3438	–0.0395		–	0.3671	–0.0161		–
JBL	0.3558	0.2918	–0.0640		–	0.2746	–0.0813		–
LU	0.4034	0.3572	–0.0462		–	0.4584	0.0550		+
MOT	0.4799	0.5455	0.0655		+	0.4732	–0.0068		–
MRK	0.2925	0.4781	0.1856		+	0.3477	0.0552		+
NOK	0.5072	0.4684	–0.0388		–	0.5870	0.0798		+
PCS	0.3787	0.2857	–0.0930		–	0.3636	–0.0151		–
Q	0.3899	0.3611	–0.0288		–	0.4997	0.1098		+
RD	0.4798	0.2727	–0.2071		–	0.5238	0.0440		+
RIG	0.4632	0.5200	0.0568		+	0.5417	0.0785		+
SAP	0.3223	0.5000	0.1778		+	0.3200	–0.0023		–
SBC	0.3870	0.5556	0.1685		+	0.2308	–0.1562		–
SGP	0.3744	0.3810	0.0066		+	0.1667	–0.2077	*	–
SLR	0.3533	0.2381	–0.1152		–	0.5000	0.1467		+
T	0.4204	0.5599	0.1395		+	0.4163	–0.0041		–
VZ	0.4081	0.4286	0.0204		+	0.4800	0.0719		+

* means significant at 5% and ** means significant at 1%.

4.1.2 DELTA (δ), GAMMA (γ), AND BETA (β)

In Table 3, we notice the mean of δ appears to increase in the up-recommendation period and decrease in the down-recommendation period, although the statistics are insignificant: $p = 0.1667$ and 0.6259 respectively. This does not go along with the intuitive expectation of higher probability for good news (1 – δ) in the up-recommendation period and higher probability for bad news (δ) in the down-recommendation period, compared to the no-recommendation period.

Table 5 gives the change in delta, the probability of bad news given the occurrence of some news. In the up-recommendation period, there are 14 positive changes meaning higher probability of bad news, and 16 negative changes meaning lower probability of bad news or higher probability of good news. The change in delta varies from –0.5658 to 0.9639. In the down-recommendation period, there are 11 positive changes and 19 negative changes with the change ranging from –0.8595 to 0.5953. When we check the significance of the change in δ using the likelihood ratio test (conditional probability of bad news, given the occurrence of some news), the results are quite mixed: in the up-recommendation period, there are 11 firms having significantly higher, 4 significantly lower and 15 insignificantly changed δ; and in the down-recommendation period, there are 3 higher, 5 lower and 22 insignificant.

As discussed above, we calculate γ (the unconditional probability of bad-news or probability of a bad-news day) and β (the unconditional probability of good-news or probability of a good-news day) respectively. The descriptive summary of these are given in Table 6. Gamma ranges from 0.0000 to 0.7252 in the no-recommendation period, 0.0000 to 0.8333 in the up-recommendation period and 0.0000 to 0.8387 in the down-recommendation period. The mean of gamma increases in up-recommendation and decreases in down-recommendation, although not significantly. In the up-recommendation period, the variance of gamma increases significantly. Beta ranges from 0.0000 to 0.5173 in the no-recommendation period, 0.0000 to 0.6666 in the up-recommendation period and 0.0000 to 0.6190 in the down-recommendation period. The mean insignificantly decreases in the up-recommendation and increases in the down-recommendation period. The variance of beta increases significantly in both recommendation periods, although more strongly in the up-recommendation period. This once again fails to be consistent with our hypothesis, where we expect a higher probability for a good-news day (β) or a lower probability for a bad-news day (γ) in the up-recommendation period, and a higher probability for a bad-news day or a lower probability for a good-news day in the down-recommendation period, compared to the no-recommendation period. However the greater variances of δ, γ and β confirm that on the days the analysts change their recommendations, the market does have some confusion about the information signals of the firms.

Checking the significance of the change in γ (unconditional probability of bad-news) and β (unconditional probability of good-news) gives us the results shown in Table 7 and Table 8. In the up-recommendation period, we have 8 significantly higher, 4 significantly lower and 18 insignificant changes in γ; and 4 significantly higher, 6 significantly lower and 20 insignificant changes in β. If as discussed above, we treat either higher β and/or lower γ in the up-recommendation period as the time when analysts are accurate, we would get 8 significantly accurate firms, 7 significantly inaccurate and 15 insignificant.

Table 5

Analysis of delta (δ)

Ticker	no recommen-dation	up recommendation				down recommendation			
	estimate	estimate	change			estimate	change		
AOL’	0.3998	0.8948	0.4950	**	+	0.1334	–0.2664	*	–
APC	0.1175	0.4223	0.3048	**	+	0.0002	–0.1173		–
AT	0.0169	0.0000	–0.0168		–	0.0001	–0.0168		–
AWE	1.0000	1.0000	0.0000		–	1.0000	0.0000		–
BP	0.0248	0.3750	0.3502	**	+	0.0000	–0.0248		–
BR	0.3004	0.2488	–0.0516		–	0.0000	–0.3004		–
BSX	0.0237	0.5000	0.4764	**	+	0.0000	–0.0237		–
CC	0.0237	0.0000	–0.0237		–	0.0000	–0.0237		–
COF	0.0000	0.0000	0.0000		+	0.0000	0.0000		+
DNA	0.5769	1.0000	0.4231	*	+	0.0000	–0.5769	**	–
DVN	0.4498	0.3334	–0.1165		–	0.7225	0.2727		+
EDS	0.1915	0.1111	–0.0804		–	0.1250	–0.0665		–
EOG	0.3964	0.0000	–0.3964	**	–	0.7793	0.3829	**	+
GDT	0.3375	0.4167	0.0792		+	0.0000	–0.3375	**	–
GPS	0.1842	0.0909	–0.0933		–	0.1816	–0.0026		–
JBL	0.2908	0.1428	–0.1480		–	0.6622	0.3714		+
LU	0.3497	0.2000	–0.1497		–	0.5455	0.1958		+
MOT	0.2777	0.0000	–0.2777	**	–	0.1688	–0.1089		–
MRK	0.4080	1.0000	0.5920	**	+	0.7504	0.3423		+
NOK	0.1095	0.1334	0.0239		+	0.0000	–0.1095		–
PCS	0.1914	0.0000	–0.1914	*	–	0.0833	–0.1081		–
Q	0.2689	0.0769	–0.1920		–	0.1047	–0.1642		–
RD	0.0361	1.0000	0.9639	**	+	0.0000	–0.0361		–
RIG	0.5658	0.0000	–0.5658	**	–	0.0769	–0.4888	**	–
SAP	0.1539	0.0000	–0.1539		–	0.6249	0.4710	**	+
SBC	0.8595	1.0000	0.1405	*	+	0.0000	–0.8595	**	–
SGP	0.2313	0.1250	–0.1063		–	0.2500	0.0187		+
SLR	0.3619	1.0000	0.6381	**	+	0.3637	0.0019		+
T	0.2521	0.7144	0.4623	**	+	0.3993	0.1472		+
VZ	0.0713	0.3333	0.2620	*	+	0.6667	0.5953	**	+

* means significant at 5% and ** means significant at 1%.

In the down-recommendation period, there are 4 higher, 5 lower and 21 insignificant with γ, and 3 higher, 1 lower and 26 insignificant with β. As we can see, different from the mixed result in the up-recommendation period, insignificant changes dominate in the down-recommendation period. But again, we find 4 significantly accurate, 6 significantly inaccurate, and 20 insignificant firms.

The above findings fail in supporting the hypotheses on the accuracy of financial analysts, and indicate an inaccurate or at best a spurious ability for typical analysts. We regard this as support for Events (2) and (4) as discussed above, where Event (2) refers to the situation when analysts make inaccurate recommendations, but investors believe them to be accurate, and Event (4) refers to when analysts make inaccurate recommendations, and investors correctly believe these recommendations to be inaccurate.

Table 6

Descriptive summary of gamma and beta across the thirty firms

		In the no-recommendation period	In the up-recommendation period	In the down-recommendation period
gamma $\gamma = \alpha * \delta$	minimum	0.0000	0.0000	0.0000
	maximum	0.7252	0.8333	0.8387
	mean	0.1232	0.1664 (0.1433)	0.1200 (0.8985)
	Standard Deviation	0.1386	0.2155 (0.0203)**	0.1829 (0.1405)
beta $\beta = \alpha * (1-\delta)$	minimum	0.0000	0.0000	0.0000
	maximum	0.5173	0.6666	0.6190
	mean	0.3008	0.2732 (0.4015)	0.3303 (0.2065)
	Standard Deviation	0.1228	0.1903 (0.0214)**	0.1766 (0.0551)*

* means significant at 10% and ** means significant at 5%.

Table 7

Analysis of gamma (γ)

Ticker	no recommen-dation	up recommendation				down recommendation			
	$\gamma = \alpha*\delta$	$\gamma = \alpha*\delta$	change			$\gamma = \alpha*\delta$	change		
AOL'	0.2057	0.6538	0.4481	**	+	0.0690	–0.1367	*	–
APC	0.0606	0.2408	0.1803		+	0.0001	–0.0605		–
AT	0.0068	0.0000	–0.0067		–	0.0001	–0.0067		–
AWE	0.7252	0.8333	0.1082		+	0.8387	0.1135		+
BP	0.0110	0.1429	0.1319	**	+	0.0000	–0.0110		–
BR	0.1016	0.0736	–0.0280		–	0.0000	–0.1016		–
BSX	0.0113	0.1250	0.1137	**	+	0.0000	–0.0113		–
CC	0.0112	0.0000	–0.0112		–	0.0000	–0.0112		–
COF	0.0000	0.0000	0.0000		+	0.0000	0.0000		+
DNA	0.1884	0.1818	–0.0066		–	0.0000	–0.1884	**	–
DVN	0.1927	0.1333	–0.0594		–	0.3696	0.1769	*	+
EDS	0.0582	0.0385	–0.0197		–	0.0357	–0.0225		–
EOG	0.1560	0.0000	–0.1560	**	–	0.4148	0.2589	**	+
GDT	0.1561	0.2000	0.0439		+	0.0000	–0.1561	**	–
GPS	0.0706	0.0313	–0.0393		–	0.0667	–0.0039		–
JBL	0.1035	0.0417	–0.0618		–	0.1818	0.0783		+
LU	0.1411	0.0714	–0.0696		–	0.2501	0.1090		+
MOT	0.1333	0.0000	–0.1333	*	–	0.0799	–0.0534		–
MRK	0.1194	0.4781	0.3587	**	+	0.2609	0.1416		+
NOK	0.0555	0.0625	0.0070		+	0.0000	–0.0555		–
PCS	0.0725	0.0000	–0.0725	*	–	0.0303	–0.0422		–
Q	0.1049	0.0278	–0.0771		–	0.0523	–0.0525		–
RD	0.0173	0.2727	0.2554	**	+	0.0000	–0.0173		–
RIG	0.2620	0.0000	–0.2620	**	–	0.0417	–0.2204	**	–
SAP	0.0496	0.0000	–0.0496		–	0.2000	0.1504	*	+
SBC	0.3327	0.5556	0.2229	*	+	0.0000	–0.3327	**	–
SGP	0.0866	0.0476	–0.0390		–	0.0417	–0.0449		–
SLR	0.1279	0.2381	0.1102		+	0.1819	0.0540		+
T	0.1060	0.4000	0.2940	**	+	0.1662	0.0602		+
VZ	0.0291	0.1429	0.1137	*	+	0.3200	0.2909	**	+

*means significant at 5% and ** means significant at 1%.

Table 8

Analysis of beta (β)

Ticker	no recommen-dation	up recommendation				down recommendation			
	$\beta = \alpha^* (1-\delta)$	$\beta = \alpha^* (1-\delta)$	change			$\beta = \alpha^* (1-\delta)$	change		
AOL'	0.3089	0.0769	–0.2320	**	–	0.4482	0.1394	*	+
APC	0.4549	0.3295	–0.1254		–	0.4999	0.0450		+
AT	0.3953	0.6666	0.2713		+	0.5454	0.1501		+
AWE	0.0000	0.0000	0.0000		+	0.0000	0.0000		+
BP	0.4322	0.2381	–0.1941	**	–	0.5454	0.1132		+
BR	0.2365	0.2222	–0.0143		–	0.4169	0.1804		+
BSX	0.4660	0.1250	–0.3410	**	–	0.4615	–0.0045		–
CC	0.4608	0.5714	0.1106		+	0.6190	0.1583		+
COF	0.5173	0.4167	–0.1006		–	0.5500	0.0327		+
DNA	0.1382	0.0000	–0.1382		–	0.2800	0.1418	**	+
DVN	0.2357	0.2667	0.0309		+	0.1420	–0.0937	*	–
EDS	0.2457	0.3077	0.0620		+	0.2500	0.0043		+
EOG	0.2375	0.4783	0.2408	**	+	0.1175	–0.1200	**	–
GDT	0.3065	0.2800	–0.0265		–	0.3548	0.0483	**	+
GPS	0.3127	0.3125	–0.0002		–	0.3005	–0.0122		–
JBL	0.2524	0.2501	–0.0022		–	0.0927	–0.1596		–
LU	0.2623	0.2857	0.0234		+	0.2083	–0.0540		–
MOT	0.3467	0.5455	0.1988	*	+	0.3933	0.0466		+
MRK	0.1732	0.0000	–0.1732	**	–	0.0868	–0.0864		–
NOK	0.4517	0.4059	–0.0458		–	0.5870	0.1354		+
PCS	0.3062	0.2857	–0.0205	*	–	0.3333	0.0271		+
Q	0.2851	0.3333	0.0483		+	0.4474	0.1623		+
RD	0.4625	0.0000	–0.4625	**	–	0.5238	0.0613		+
RIG	0.2011	0.5200	0.3189	**	+	0.5000	0.2989	**	+
SAP	0.2727	0.5000	0.2274		+	0.1200	–0.1526	*	–
SBC	0.0544	0.0000	–0.0544	*	–	0.2308	0.1765	**	+
SGP	0.2878	0.3333	0.0456		+	0.1250	–0.1628		–
SLR	0.2254	0.0000	–0.2254		–	0.3181	0.0927		+
T	0.3144	0.1599	–0.1545	**	–	0.2500	–0.0644		–
VZ	0.3790	0.2857	–0.0933	*	–	0.1600	–0.2190	**	–

*means significant at 5% and ** means significant at 1%.

4.1.3 EPSILON BUY (ε_b), EPSILON SELL (ε_s) AND MU (μ)

ε_b and ε_s are the arrival rates of uninformed sellers and buyers, and μ is the arrival rate of informed traders. These three parameters relate to trader composition. As we can see in Table 3, the variances of each component are not significantly different between the no-recommendation period and either recommendation period. However, the means show significant increase in both recommendation periods. This suggests that the market takes the days when analysts release recommendations as information events, responding with more trades.

A. In the up-recommendation period

Now we look at the difference of those parameters between recommendation and no-recommendation periods for each firm. The likelihood ratio test for ε_b gives the most significant increases: 23 out of 30 firms, meaning the arrival rate of buys are significantly greater when analysts increase their recommendations. This suggests that investors generally believe analysts, which supports Events (1) and (2). But if we shift the attention to the other 7 firms, where 4 firms show no significant change and 3 firms show significant decrease, we find something more interesting. The 3 firms with significantly lower buys (EOG, MOF and RIG) are among the ones where analysts are accurate, higher β or lower γ in the up-recommendation period. As we discuss above, generally speaking, analysts are not good at forecasting the occurrence of an information event and at timing their recommendations. But when they do in fact do a good job, investors choose not to believe them and do the opposite. However when analysts are definitely wrong by giving an up-recommendation on the days with higher probabilities of bad-news or lower probabilities of good-news, the uninformed buys increase with no exception. So putting this together, we conclude that most of the time investors believe analysts' recommendations, but sometimes they do not. Unfortunately investors do not know when they should and should not believe analyst recommendations, and quite often they make bad choices by believing when they should not believe and vice versa.

Furthermore, we find that the arrival rate of uniformed sells show 18 significant increases, 6 significant decreases and 6 insignificant changes, and the arrival rate of informed traders shows 20 significant increases, 5 significant decreases and 5 insignificant changes. To test the null hypothesis there are no more increases (either no change[17] or decrease) of each component in the recommendation period, we use the sign test, which is a common nonparametric method to test hypotheses about the median of a population distribution when we have before-and-after matched pairs of data for a sample. The assumption we have for the test is that the probability of a plus sign and a minus sign are equally likely (50%) for each and the distribution is binomial. The hypotheses are rejected for ε_b and μ at the 5% significance level (p-value equal to 0.0007 and 0.0214 respectively). But for the uninformed sells ε_s, we failed to reject the null (p-value 0.1002). So we conclude that although the mean of each component of trade increases significantly in both recommendation periods as shown in Table 3, for individual firms, we can only expect a higher arrival rate of uninformed buyers and informed traders in the up-recommendation period. The increase in arrival rate of the uninformed seller is not significant, (although this is close to being marginally significant).

[17] Here we treat the insignificant changes as zero. We double check this using the original sign, and it turns out that all trader components increase in both up- and down-recommendation periods, which means higher arrival rates in recommendation periods. This is consistent with the finding of Easley et al. (1998) that there were significant differences in both informed and uninformed arrival rates across the stocks with high and low analyst following. And we conclude that the arrival rate of all traders increase on the recommendation days, the only issue is whether the increase is significant or insignificant.

Table 9

Analysis of epsilon buy (ε_b)

Ticker	no recommendation	up recommendation					down recommendation				
	estimate	estimate	Δ	% Δ			estimate	Δ	% Δ		
AOL'	1459	1609	150	10%	**	+	1422	–37	–3%	**	–
APC	869	969	100	12%	**	+	846	–22	–3%	*	–
AT	419	405	–14	–3%		–	402	–17	–4%	*	–
AWE	922	1035	114	12%	**	+	1011	89	10%	**	+
BP	420	526	106	25%	**	+	429	9	2%		+
BR	587	634	47	8%	**	+	551	–36	–6%	**	–
BSX	397	670	274	69%	**	+	490	94	24%	**	+
CC	385	468	83	21%	**	+	376	–10	–2%		–
COF	764	1062	297	39%	**	+	1000	236	31%	**	+
DNA	668	941	273	41%	**	+	718	51	8%	**	+
DVN	452	456	4	1%		+	542	90	20%	**	+
EDS	652	798	146	22%	**	+	746	94	14%	**	+
EOG	473	422	–51	–11%	**	–	619	145	31%	**	+
GDT	648	671	23	3%	**	+	658	10	2%		+
GPS	728	815	87	12%	**	+	881	153	21%	**	+
JBL	733	729	–4	–1%		–	785	53	7%	*	+
LU	1121	1194	73	6%	**	+	1212	91	8%	**	+
MOT	1181	1116	–65	–5%	**	–	1278	97	8%	**	+
MRK	1136	1505	369	33%	**	+	1412	276	24%	**	+
NOK	1079	1132	52	5%	**	+	982	–97	–9%	**	–
PCS	738	814	76	10%	**	+	853	115	16%	**	+
Q	827	931	104	13%	**	+	823	–4	0%		–
RD	765	1119	354	46%	**	+	816	51	7%	**	+
RIG	1003	909	–94	–9%	**	–	973	–30	–3%	**	–
SAP	222	218	–4	–2%		–	316	94	42%	**	+
SBC	1400	1570	170	12%	**	+	1383	–17	–1%		–
SGP	915	993	77	8%	**	+	967	52	6%	**	+
SLR	798	922	124	16%	**	+	768	–30	–4%	**	–
T	902	997	95	11%	**	+	990	88	10%	**	+
VZ	1215	1500	285	23%	**	+	1654	439	36%	**	+

*means significant at 5% and ** means significant at 1%.

Table 10

Analysis of epsilon sell (ε_s)

Ticker	no recom-mendation	up recommendation					down recommendation				
	estimate	esti-mate	Δ	% Δ			esti-mate	Δ	% Δ		
AOL'	1402	1175	–227	–16%	**	–	1493	91	6%	**	+
APC	792	789	–4	0%		–	879	87	11%	**	+
AT	524	569	45	9%	**	+	648	124	24%	**	+
AWE	375	479	104	28%	**	+	405	30	8%	**	+
BP	514	467	–47	–9%	**	–	532	18	4%	**	+
BR	506	503	–3	–1%		–	562	56	11%	**	+
BSX	509	545	36	7%	**	+	549	39	8%	**	+
CC	499	671	171	34%	**	+	623	123	25%	**	+
COF	917	1150	233	25%	**	+	1131	214	23%	**	+
DNA	501	564	63	13%	**	+	608	107	21%	**	+
DVN	336	355	19	6%	**	+	377	41	12%	**	+
EDS	623	741	118	19%	**	+	736	114	18%	**	+
EOG	378	464	85	23%	**	+	414	36	9%	**	+
GDT	603	593	–10	–2%		–	757	155	26%	**	+
GPS	654	736	82	12%	**	+	776	122	19%	**	+
JBL	611	675	64	10%	**	+	596	–15	–2%	*	–
LU	1281	1279	–2	0%		–	1210	–70	–5%		–
MOT	1177	1348	171	14%	**	+	1276	99	8%	**	+
MRK	1075	1012	–64	–6%		–	1139	64	6%	**	+
NOK	1149	1159	11	1%		+	1173	24	2%	**	+
PCS	700	832	132	19%	**	+	836	137	20%	**	+
Q	882	1019	137	16%	**	+	1011	130	15%	**	+
RD	865	805	–60	–7%	**	–	992	127	15%	**	+
RIG	779	943	164	21%	**	+	1006	226	29%	**	+
SAP	214	298	84	39%	**	+	215	1	1%		+
SBC	1181	1129	–52	–4%	**	–	1449	268	23%	**	+
SGP	883	1018	136	15%	**	+	978	95	11%	**	+
SLR	715	644	–70	–10%	**	–	732	18	2%	**	+
T	1063	962	–101	–10%	**	–	1126	62	6%	**	+
VZ	1307	1525	218	17%	**	+	1353	47	4%	**	+

*means significant at 5% and ** means significant at 1%.

Table 11

Analysis of mu (µ)

Ticker	no recommendation	up recommendation					down recommendation				
	estimate	estimate	Δ	% Δ			estimate	Δ	% Δ		
AOL'	472	517	45	10%	**	+	556	84	18%	**	+
APC	300	245	–56	–19%	**	–	490	190	63%	**	+
AT	427	346	–81	–19%	**	–	517	91	21%	**	+
AWE	708	687	–21	–3%		–	758	50	7%	**	+
BP	372	329	–43	–12%	**	–	327	–45	–12%	**	–
BR	313	315	2	1%		+	392	80	25%	**	+
BSX	373	446	73	20%	**	+	424	51	14%	**	+
CC	465	672	207	45%	**	+	529	64	14%	**	+
COF	683	770	87	13%	**	+	784	101	15%	**	+
DNA	257	546	289	112%	**	+	370	113	44%	**	+
DVN	211	223	12	6%		+	185	–26	–12%	**	–
EDS	324	416	92	28%	**	+	505	180	56%	**	+
EOG	223	280	57	26%	**	+	216	–7	–3%		–
GDT	304	395	90	30%	**	+	481	177	58%	**	+
GPS	340	399	59	17%	**	+	456	116	34%	**	+
JBL	297	363	66	22%	**	+	263	–34	–12%	*	–
LU	625	631	7	1%		+	522	–102	–16%	**	–
MOT	354	455	102	29%	**	+	288	–66	–19%	**	–
MRK	540	701	161	30%	**	+	550	10	2%		+
NOK	356	390	34	10%	**	+	465	109	31%	**	+
PCS	359	616	258	72%	**	+	555	197	55%	**	+
Q	378	544	166	44%	**	+	540	161	43%	**	+
RD	437	625	188	43%	**	+	551	114	26%	**	+
RIG	366	517	151	41%	**	+	401	35	10%	**	+
SAP	201	268	66	33%	**	+	201	–1	0%		–
SBC	583	529	–55	–9%	**	–	596	13	2%		+
SGP	337	511	174	52%	**	+	659	321	95%	**	+
SLR	352	486	134	38%	**	+	348	–4	–1%		–
T	374	334	–40	–11%	**	–	318	–56	–15%	**	–
VZ	642	651	8	1%		+	525	–117	–18%	**	–

*means significant at 5% and ** means significant at 1%.

B. In the down-recommendation period

When analysts make downward adjustments to their recommendations, the average arrival rate of uninformed sellers ε_s increases a lot. There are 27 increases, 1 decrease and 2 with no significant change among the 30 firms in the down-recommendation period, which rejects the null hypothesis that there are no more increases (either no change or decrease) of each component in the recommendation period significantly (p-value = 0.0000) and strongly supports more increases. The statistics of the sign test for ε_b and μ have p-values of 0.04937 and 0.1002 respectively. These mean that whenever analysts adjust their recommendations downward, the market can expect more uninformed buys and more uninformed sells, but not necessarily more informed, (although this is close to being marginally significant).

The poor decision that uninformed traders make about when to believe analysts also shows up here. Analysts are accurate when they make a downward adjustment to their recommendation on days with higher probability of bad-news, γ, or lower probability of good-news, β. In Table 9, we can see that in those 4 cases when analysts are accurate (DVN, EOG, SAP, and VZ), the uninformed buyers all increased; however, in the 6 cases when analysts are inaccurate (AOL, COF, GDT, Q, RIG, and SBC), the uninformed sellers all increase. This once again shows that the uninformed investors unfortunately tend to believe analysts when they should not.

Our observation about the poor choices investors make is consistent with the concern of the CFA institute, which mentioned in its *Standards of Practice Handbook* (ninth edition 2005) that "one of the ways that research analysts have coped with these pressures[18] in the past is to use subtle and ambiguous language in their recommendations or to temper the tone of their research reports. Such subtleties are lost on some investors who reasonably expect research reports and recommendations to be straightforward and transparent and to communicate clearly an analyst's views based on unbiased analysis and independent judgement."

As to the significant increase of informed trading in the up-recommendation period, we suspect those are only due to increased "camouflaging" ability. More trades by uninformed buyers and sellers provide cover for informed traders to transact more without revealing too much of their information to the market maker. As some studies indicate that a monopolist informed trader may camouflage his trading activity by splitting one large trade into several small trades (Kyle 1985, Admati and Pfleiderer 1988). Barclay and Warner (1993) proposed a "stealth trading" hypothesis stating that during a period of time, the informed traders attempt to camouflage their private information by engaging in multiple smaller trades rather than to achieve their desired portions by one or two larger trades. That is to say, to avoid giving away their information, informed traders have to avoid trading too much. The amount of trading that they can get away with depends on the volume of uninformed trading. Since recommendation changes increase the order flow from uninformed traders, there is a possibility that the quantity of informed trading would also increase (provided that an information event has in fact occurred). Thus days when analysts announce their recommendations provide a good opportunity for the informed traders to camouflage their trading, and the more trades observed in the

[18] Pressure comes from both external sources and their own firms, and it may jeopardize their ability to act with independence and objectivity.

up-recommendation period hint that informed traders are exploiting the opportunities. We look at this more carefully in the next section.

Table 12

The change of each parameter in recommendation periods

Ticker	In the up-recommendation period							In the down-recommendation period						
	α	δ	γ = α*δ	β = α*(1–δ)	ε_b	ε_s	μ	α	δ	γ = α*δ	β = α*(1–δ)	ε_b	ε_s	μ
AOL/TWX	* +	** +	** +	** –	** +	** –	** +	+	* –	* –	+	** –	** +	** +
APC	+	** +	+	–	** +	–	** –	–	–	–	+	* –	** +	** +
AT	* +	–	–	** +	–	** +	** –	+	–	–	+	* –	** +	** +
AWE	+	–	+	+	** +	** +	–	+	–	+	+	** +	** +	** +
BP	–	** +	** +	–	** +	** –	** –	+	–	–	+	+	** +	** –
BR	–	–	–	–	** +	–	+	+	–	–	+	** –	** +	** +
BSX	* –	** +	** +	** –	** +	** +	** +	–	–	–	–	** +	** +	** +
CC	+	–	–	+	** +	** +	** +	+	–	–	+	–	** +	** +
COF	–	+	+	–	** +	** +	** +	+	+	+	+	** +	** +	** +
DNA	–	* +	–	* –	** +	** +	** +	–	** –	** –	+	** +	** +	** +
DVN	–	–	–	+	+	** +	+	+	+	* +	–	** +	** +	** –
EDS	+	–	–	+	** +	** +	** +	–	–	–	+	** +	** +	** +
EOG	+	** –	** –	* +	** –	** +	** +	+	** +	** +	–	** +	** +	–
GDT	+	+	+	–	** +	–	** +	–	** –	** –	+	+	** +	** +
GPS	–	–	–	–	** +	** +	** +	–	–	–	–	** +	** +	** +
JBL	–	–	–	–	–	** +	** +	–	+	+	–	* +	* –	* –
LU	–	–	–	+	** +	–	+	+	+	+	–	** +	–	** –
MOT	+	** –	* –	+	** –	** +	** +	–	–	–	+	** +	** +	** –
MRK	+	** +	** +	** –	** +	–	** +	+	+	+	–	** +	** +	+
NOK	–	+	+	–	** +	+	** +	+	–	–	+	** –	** +	** +
PCS	–	* –	* –	–	** +	** +	** +	–	–	–	+	** +	** +	** +
Q	–	–	–	+	** +	** +	** +	+	–	–	* +	–	** +	** +
RD	–	** +	** +	** –	** +	** –	** +	+	–	–	+	** +	** +	** +

Table 12 (cont'd)

The change of each parameter in recommendation periods

Ticker	In the up-recommendation period							In the down-recommendation period						
	α	δ	γ = α*δ	β = α* (1–δ)	ε_b	ε_s	μ	α	δ	γ = α*δ	β = α* (1–δ)	ε_b	ε_s	μ
RIG	+	** –	** –	** +	** –	** +	** +	+	** –	** –	** +	** –	** +	** +
SAP	+	–	–	* +	–	** +	** +	–	** +	* +	–	** +	+	–
SBC	+	* +	* +	–	** +	** –	** –	–	** –	** –	** +	–	** +	+
SGP	+	–	–	+	** +	** +	** +	* –	+	–	–	** +	** +	** +
SLR	–	** +	+	** –	** +	** –	** +	+	+	+	+	** –	** +	–
T	+	** +	** +	–	** +	** –	** –	–	+	+	–	** +	** +	** –
VZ	+	* +	* +	–	** +	** +	+	+	** +	** +	* –	** +	** +	** –
Significant increase	2	11	8	4	23**	18	20*	0	3	4	3	19*	27**	18
Significant decrease	1	4	4	6	3	6	5	1	5	5	1	6	1	7
Insignificant change	27**	15	18	20	4	6	5	29**	22**	21**	26**	5	2	5

* means significant at 5% and ** means significant at 1%.

4.2 PIN AND CONDITIONAL PIN

To make sure that the increase in informed trading is merely "camouflaging" behaviour of informed traders, we check whether there is significant change in the probability of information-based trading in different periods. If the probabilities change in the recommendation period, then we cannot conclude that analysts just give informed traders a good time to camouflage their intent. And this, as we discussed above, may result in different behaviour of specialists on recommendation days. However, if the probabilities don't change in either recommendation period, then we would say that the behaviour of specialists doesn't change on recommendation days. Furthermore, this may be taken as evidence of market efficiency. Since we know analysts' recommendations are based on public information, the announcement of their recommendations should have no effect on the probabilities of informed trading.

Table 13 provides the descriptive summary of the unconditional and conditional probabilities we calculate with the parameters estimated above. The unconditional probability of information-based trading (PIN) ranges from 5.7% to 25.6% in the no-recommendation period. In recommendation period, the range widens: 4.8% to 26.0% in the up-recommendation period and 4.0 to 29.2% in down-recommendation. This is consistent with the great variance of alpha, delta, gamma and beta, the probabilities related to the occurring of private information events. The mean of PIN increases in both up- and down-recommendation periods, insignificantly in the up-recommendation period and significantly (with *p*-value 0.0286 as shown in the bracket below the mean) in the down-recommendation period. Once more, this suggests that down-recommendations are more credible or accurate than up-recommendations.

The conditional probabilities increase the range in the recommendation periods too. PIN|sell ranges from 0.0% to 47.4% in the no-recommendation period, 0.0% to 49.1% in the up-recommendation period and 0.0% to 54.7% in the down-recommendation period. PIN|buy ranges from 0.0% to 25.2% in the no-recommendation period, 0.0% to 33.7% in the up-recommendation period and 0.0% to 36.2% in the down-recommendation period. Although the range of PIN|sell is wider than PIN|buy, the mean of PIN|sell is smaller than the mean of PIN|buy, consistent with the notion that buyer-initiated trades are more informative than seller-initiated trades. Furthermore, the mean of PIN|sell increases in the up-recommendation period, and the mean of PIN|buy increases in the down-recommendation period, although both are weakly significant (*p*-value equals to 0.0980 and 0.0814 respectively). This goes along with our hypothesis that specialists would give a higher PIN|sell in the up-recommendation period and a higher PIN|buy in the down-recommendation period, based on his suspicion that on recommendation days orders in the opposite direction of recommendation are more likely to be information-based trades. Besides, PIN|buy decreases in the up-recommendation period as we expected, although insignificantly while PIN|sell has no change in the down-recommendation period.

The changes in PIN and conditional PIN in the recommendation periods are given in Table 14. As we discussed above, if the analysts' recommendations are associated with information events, we would see a high PIN in both recommendation periods. And if specialists know that uninformed investors on average believe analysts, on recommendation days there would be an increase in trading in the direction of the recommendation, and orders in the opposite direction of recommendation are more likely to be information-based trades, they would use a higher PIN|sell and a lower PIN|buy in the up-recommendation period to set up the bid and ask quote. In the down-recommendation period, lower PIN|sell and higher PIN|buy. The sign of the change of those probabilities are just as expected: unconditional PIN increases in both up- and down- recommendation periods, in the up-recommendation period, PIN|sell increases and PIN|buy decreases, while in the down-recommendation period, PIN|buy increases and PIN|sell has no change. However, they are all statistically insignificant according to the *t*-test[19].

The sign test we used to check for robustness gives a similar insignificant result. The number of increases of PIN, PIN|sell, and PIN|buy are 16 (*p*-value=0.2923), 15 and 16 respectively in the up-recommendation period and 18 (*p*-value=0.1002), 12 and 18 respectively in the down period. This shows in general the specialists would not take the announcement of analysts' recommendation into significant consideration when they set up bid and ask prices because the probability of information-based trading, both unconditional and conditional, does not change substantially on recommendation days.

As a further test of the indifference of specialists to analysts' recommendation in general, we check the equivalence of the arrival rates of uninformed buys and uninformed sells in recommendation periods, and report the result in Table 15. The difference between the arrival rates of buy orders and sell orders, although quite significant, has various signs, giving 18 significantly positive and 11 significantly negative in the no-recommendation period, 11 significantly positive and 12 significantly negative in the up-recommendation period, and 10 significantly positive and 15 significantly negative in the down-recommendation period. The sign test on the direction of the differences gives in-

[19] We use both LOGIT and TOBIT transformation to do the statistics test whether they are significantly different from zero, because the delta of a probability only has the value between –1 to 1, and it's improper to assume a *t*-distribution. However, only the result using LOGIT transformation is reported in Table 14.

significant results in each period, showing that there is no difference between the arrival rates of buys and sells from the perspective of each firm. Across the thirty firms, the mean of the difference in each period is slightly positive, but insignificantly different from zero. Although as we can see, the average of $\varepsilon_b - \varepsilon_s$ increases in the up-recommendation period and decreases in the down-recommendation period, referring to more buys in the up-recommendation period and more sells in the down-recommendation period, as we expected, the changes are all insignificantly different from zero. So we conclude that the arrival rates of uninformed buys and sells have no significant difference in recommendation periods. This also suggests that the specialists would not behave any differently on recommendation days.

The insignificant difference between probabilities of information-based trading in recommendation periods, and the corresponding lack of differential behaviour from specialists implied by it, counters our suspicion of asymmetry in bid discounts and ask premiums on recommendation days. So the optimism of financial analysts observed in the market does not seem to come from this possibility.

Table 13

Descriptive summary of PIN, PIN|sell, and PIN|buy across the thirty firms

		In the no-recommendation period	In the up-recommendation period	In the down-recommendation period
PIN	minimum	5.7%	4.8%	4.0%
	maximum	25.6%	26.0%	29.2%
	mean	9.2%	9.8% (0.2524)	10.1% (0.0286)**
	Standard Deviation	4.2%	4.8% (0.4589)	5.4% (0.1776)
PIN|sell	minimum	0.0%	0.0%	0.0%
	maximum	47.4%	49.1%	54.7%
	mean	4.8%	6.5% (0.0980)*	4.8% (0.9964)
	Standard Deviation	8.5%	10.0% (0.3752)	10.3% (0.3040)
PIN|buy	minimum	0.0%	0.0%	0.0%
	maximum	25.2%	33.7%	36.2%
	mean	10.7%	10.3% (0.8072)	12.5% (0.0814)*
	Standard Deviation	6.3%	8.9% (0.0682)*	9.0% (0.0654)*

* means significant at 10% and ** means significant at 5%.

Table 14

The change of probabilities in recommendation periods

Ticker	Up- vs. no-recommendation period						Down- vs. no-recommendation period					
	Δ PIN		Δ PIN/sell		Δ PIN/buy		Δ PIN		Δ PIN/sell		Δ PIN/buy	
AOL/TWX	4.2%	+	14.8%	+	–5.7%	–	1.0%	+	–3.3%	–	5.1%	+
APC	–0.9%	–	4.0%	+	–5.1%	–	3.2%	+	–1.7%	–	6.6%	+
AT	4.9%	+	–0.3%	–	10.7%	+	5.5%	+	–0.3%	–	10.7%	+
AWE	0.4%	+	1.7%	+	0.0%	+	3.6%	+	7.3%	+	0.0%	+
BP	–3.1%	–	5.4%	+	–11.1%	–	1.2%	+	–0.5%	–	3.3%	+
BR	–1.1%	–	–1.0%	–	–0.8%	–	3.3%	+	–3.9%	–	9.1%	+
BSX	–7.2%	–	5.1%	+	–17.6%	–	–0.5%	–	–0.5%	–	–1.2%	–
CC	4.9%	+	–0.5%	–	8.5%	+	5.2%	+	–0.5%	–	11.0%	+
COF	–4.2%	–	0.0%	+	–6.9%	–	–0.2%	–	0.0%	+	–0.2%	–
DNA	–1.0%	–	2.6%	+	–3.8%	–	0.2%	+	–6.4%	–	5.7%	+
DVN	–0.4%	–	–2.3%	–	1.3%	+	–0.5%	–	4.7%	+	–3.9%	–
EDS	1.2%	+	–0.6%	–	2.4%	+	1.1%	+	–0.5%	–	1.9%	+
EOG	3.3%	+	–5.8%	–	11.5%	+	1.1%	+	8.5%	+	–4.6%	–
GDT	2.4%	+	2.8%	+	0.6%	+	–0.1%	–	–5.2%	–	5.2%	+
GPS	–0.5%	–	–1.3%	–	0.3%	+	0.4%	+	0.1%	+	0.3%	+
JBL	–0.4%	–	–1.9%	–	1.0%	+	–2.1%	–	2.2%	+	–5.0%	–
LU	–1.1%	–	–2.3%	–	0.5%	+	–0.2%	–	2.9%	+	–3.1%	–
MOT	2.2%	+	–3.1%	–	7.8%	+	–1.5%	–	–1.6%	–	–0.8%	–
MRK	4.7%	+	15.6%	+	–5.6%	–	0.4%	+	4.5%	+	–3.1%	–
NOK	–0.2%	–	0.3%	+	–0.8%	–	3.4%	+	–1.3%	–	7.7%	+
PCS	0.2%	+	–2.5%	–	2.3%	+	1.4%	+	–1.2%	–	3.1%	+
Q	0.8%	+	–2.2%	–	3.3%	+	4.3%	+	–1.3%	–	8.8%	+
RD	–3.5%	–	11.3%	+	–16.8%	–	2.1%	+	–0.6%	–	4.3%	+
RIG	3.5%	+	–8.4%	–	13.5%	+	1.2%	+	–7.2%	–	9.2%	+
SAP	6.9%	+	–2.4%	–	14.6%	+	–1.4%	–	7.2%	+	–8.3%	–
SBC	2.0%	+	6.7%	+	–1.6%	–	–3.1%	–	–11.0%	–	5.4%	+
SGP	1.8%	+	–0.8%	–	3.6%	+	–1.7%	–	–0.7%	–	–2.7%	–
SLR	–1.0%	–	6.0%	+	–6.9%	–	2.7%	+	1.6%	+	3.0%	+
T	1.4%	+	7.5%	+	–5.2%	–	–1.3%	–	0.9%	+	–3.1%	–
VZ	–0.7%	–	3.3%	+	–4.5%	–	–1.2%	–	8.0%	+	–9.3%	–
Mean	0.0065		0.0173		–0.0035		0.0093		0.0000		0.0184	
St. Dev	0.0303		0.0553		0.0782		0.0220		0.0447		0.0558	
p-value[1]	(0.2190)		(0.1139)		(0.4973)		(0.1959)		(0.3535)		(0.1069)	

[1] The *p*-value by using the LOGIT transformation of the probabilities.

Table 15

Difference between ε_b and ε_s (ε_b - ε_s) in each period

Ticker	No-recommendation period			Up-recommendation period			Down-recommendation period		
AOL/TWX	56	+	**	434	+	**	–71	–	**
APC	76	+	**	180	+	**	–33	–	**
AT	–106	–	**	–164	–	**	–246	+	**
AWE	546	+	**	556	+	**	606	–	**
BP	–94	–	**	60	+	**	–103	–	**
BR	81	+	**	130	+	**	–11	–	
BSX	–113	–	**	125	+	**	–58	–	**
CC	–114	–	**	–203	–	**	–247	–	**
COF	–153	–	**	–88	–	**	–131	+	**
DNA	167	+	**	376	+	**	110	+	**
DVN	116	+	**	100	+	**	165	+	**
EDS	29	+	**	57	+	**	10	+	
EOG	95	+	**	–42	–	**	204	–	**
GDT	46	+	**	78	+	**	–99	+	**
GPS	74	+	**	79	+	**	105	+	**
JBL	122	+	**	54	+	**	189	+	**
LU	–160	–	**	–85	–	**	2	+	
MOT	3	+		–232	–	**	2	+	
MRK	60	+	**	493	+	**	273	–	**
NOK	–70	–	**	–28	–	**	–191	+	**
PCS	38	+	**	–18	–	*	16	–	*
Q	–55	–	**	–88	–	**	–188	–	**
RD	–100	–	**	315	+	**	–176	–	**
RIG	224	+	**	–35	–	**	–33	+	**
SAP	8	+	**	–80	–	**	100	–	**
SBC	219	+	**	441	+	**	–65	–	**
SGP	33	+	**	–26	–	*	–11	+	
SLR	83	+	**	278	+	**	36	–	**
T	–162	–	**	35	+	**	–136	+	**
VZ	–92	–	**	–25	–		301	+	**
Significant increase	18			17			10		
Significant decrease	11			12			15		
Insignificant change	1			1			5		
Mean	28.66			89.28			10.71		
St. Dev	146.33			209.09			182.34		
p-value	(0.5776)			(0.6653)			(0.5234)		

* means significant at 5% and ** means significant at 1%.

4.3 ROBUSTNESS TEST

As a test for robustness, we use both the days when analysts announce their change of recommendations and the day before (since analysts may have observed the signals about the private information event before recommendation release, which means those parameters related to the occurrence of a private information event should change on the days before the recommendation days) as two-day recommendation periods. The change in each parameter in the 2-day recommendation periods is reported in Appendix 1. The findings about the inaccuracy of analysts hold strongly. The change in alpha is slightly greater, but still mixed in the directions and insignificant most of the time. The probabilities of a bad-news day and a good-news day, γ and β, give 8 accurate and 11 inaccurate times in the up-recommendation period, and 4 accurate and 10 inaccurate times in the down-recommendation period. Comparing this result with the result we get from one-day periods, there is no change in accurate times, but more inaccurate times. Once more the inaccuracy of financial analysts is supported.

Appendix 2 shows the change of probabilities, PIN, PIN|sell, and PIN|buy, in 2-day recommendation periods. The results are quite similar. So in the following test, we will use the results from the one-day period only.

4.4 INFLUENTIAL FACTORS ON PIN

Although the test on the change of PIN, PIN|buy and PIN|sell in the recommendation periods shows an insignificant result, meaning that specialists would generally not take the analysts' recommendation into serious consideration when they set up bid and ask prices, we are curious about whether these probabilities, PIN, PIN|buy and PIN|sell, are determined or influenced at least by some common factors. So we use regression to check the relationship, if any, between the probabilities of informed trading and some potential influential factors.

The independent variables we use in the regression model are firm size, trading volume, and return volatility. The firm size is the natural log transformation of the average of year-end total assets from 2001 to 2002 of each firm. Trading volume is the natural log of the mean of daily trading volume in the two-year period. And the volatility is the natural log of the standard deviation of daily return in the two-year period.

We understand that the industry of the firms may be relevant too. However when we use the first digit of the NASIC (as shown in Table 1), which ranges from 2 to 5, dividing the data into subgroups, the number of observations in some subgroups is too small for regression (As shown in Table 16). We report the mean of the probabilities of the firms in each industry, but we ignore them in the regression.

The linear regression models appear as follows:

$$Y_i = C + \beta_j \cdot X_j + \mu \tag{4.1}$$

and

$$Y_i = C + \sum \beta_j \cdot X_j + \mu \tag{4.2}$$

where Y_i represents PIN, PIN|buy or PIN|sell, and X_j represent size, volume and volatility. Table 17 reports the descriptive statistics of both the independent variables and dependent variables. The correlation matrix of the dependent variables is given in Table 18.

As a probability, PIN, PIN|buy and PIN|sell will take a value only between 0 and 1. This requires us to use a TOBIT model to deal with the censored data. In Table 18 we report the regression results. As shown, we run the regression with each individual dependent variable and all the dependent variables at the same time. The regression with PIN as the dependent variable gives no significant coefficients to the independent variables, meaning that the probability of information-based trading (PIN) does not seem to be influenced by the size of the firm, the trading volume, or the volatility of the daily returns. The same finding applies to PIN|sell.

The regression with PIN|buy as the dependent variable shows significant (*p*-value equals 0.0544) influence from trading volume. The negative relationship between volume and PIN|buy is still weakly significant (*p*-value equals 0.0665) when we do the multi-variable regression, where the relationship applies when all the other influential factors are held constant. This means that for a firm with larger trading volume, when a buy order comes, the probability that it is an informed trade would be comparatively smaller than that of a less frequently traded firm, while the probability that a sell order is made by an informed trader, as well as the unconditioned probability of informed trading, show no significant difference between firms with different trading volume. Intuitively, if the trading volume of a firm is large, meaning the firm is a hot issue in the market, the probability that the next trade is an informed trade is reasonably not as high (a negative sign for the relationship between PIN and volume, although insignificant), the probability that the next buyer is informed is even lower and significant, but the probability that the next seller is informed is a little bit higher (not significant, but positive sign). However, the statistics about the goodness of fit are not good: R^2 statistics are pretty low and adjusted R^2 statistics are almost all negative. This jeopardizes the economic interpretation of the weak relationships observed above. Therefore we are reluctant to draw any general conclusion based on this.

Further with the finding that the probabilities are generally not influenced by the size of the firm, the trading volume, or the volatility of the daily returns, we rank the thirty firms by size, volume, volatility respectively and divide them into three sub-groups named bottom 10, middle 10 and top 10. And then we report the mean of PIN, PIN|buy and PIN|sell of each sub-group in Table 20. The shaded part in Table 20 is consistent with the negative relationship findings between PIN|buy and volume. But still, due to the limited number of firms in our sample, we cannot generalise further on this aspect.

Since we failed to find anything with significant explanatory power for the probabilities PIN, PIN|buy and PIN|sell, the determinant or influential factor(s) of the probabilities of information-based trading opens a further research topic, which we leave for future research.

Table 16

Mean of the probabilities of different industries

	Number of Observation	PIN	PIN|buy	PIN|sell
Industry 2	5	8.10%	11.90%	11.00%
Industry 3	11	8.15%	12.23%	3.41%
Industry 4	2	11.92%	8.69%	3.85%
Industry 5	12	10.15%	9.12%	3.63%

Table 17

Descriptive statistics of the variables

	Dependent Variables			Independent Variables		
	PIN	*PIN|buy*	*PIN|sell*	*size*	*volume*	*volatility*
Mean	9.19%	10.70%	4.79%	9.9113	15.3014	1.1986
Median	7.73%	9.08%	2.92%	9.7735	15.1759	1.1830
Standard Deviation	4.16%	6.32%	8.46%	1.2198	0.9207	0.3774
Range	19.86%	25.20%	47.39%	4.2335	3.4093	1.3337
Minimum	5.74%	0.00%	0.00%	7.8050	13.8767	0.6292
Maximum	25.61%	25.20%	47.38%	12.0384	17.2860	1.9629

Table 18

Correlation matrix of the dependent variables

	Size	Volume	Volatility
Size	1.0000		
Volume	0.5556	1.0000	
Volatility	-0.1739	0.4980	1.0000

Table 19

Regression results

Dependent	Independent Variable(s)				R^2	adjusted R^2
	C	size	volume	volatility		
PIN	0.0923 (0.1379)	0.0000 (0.9955)			0.0000	–0.0741
	0.1901 (0.1290)		–0.0064 (0.4323)		0.0201	–0.0525
	0.0901 (0.0004)***			0.0015 (0.9405)	0.0002	–0.0739
	0.2545 (0.0703)*	0.0072 (0.5082)	–0.0213 (0.1395)	0.0149 (0.6367)	0.0532	–0.0983
PIN|buy	0.1521 (0.1168)	–0.0046 (0.6327)			0.0065	–0.0671
	0.4654 (0.0129)		–0.0235 (0.0544)*		0.1083	0.0422
	0.1423 (0.0003)***			–0.0303 (0.3304)	0.0285	–0.0435
	0.5313 (0.0116)**	0.0116 (0.3763)	–0.0367 (0.0665)*	–0.6193 (0.5762)	0.1361	–0.0021
PIN|sell	–0.0195 (0.8799)	0.0066 (0.6075)			–0.0191	–0.0945
	–0.2250 (0.3842)		0.0177 (0.2934)		0.0039	–0.0670
	0.0086 (0.8683)			0.0314 (0.4491)	–0.0089	–0.0836
	–0.2171 (0.4641)	–0.0005 (0.9785)	0.0173 (0.5420)	0.1047 (0.9467)	0.0043	–0.1550

*means significant at 10%, ** means significant at 5% and *** means significant at 1%.

Table 20

The mean of variables in sub-groups

	Mean					
	ln(size)	ln(volume)	volatility	PIN	PIN|buy	PIN|sell
Bottom 10	8.60			9.17%	12.57%	3.10%
Middle 10	9.84			7.86%	9.74%	7.16%
Top 10	11.30			10.56%	9.77%	4.12%
Bottom 10		14.31		9.42%	13.64%	6.47%
Middle 10		15.26		9.20%	10.06%	3.59%
Top 10		16.33		8.96%	8.40%	4.31%
Bottom 10			0.7924	8.60%	10.29%	8.10%
Middle 10			1.1851	9.25%	11.46%	2.68%
Top 10			1.6185	9.74%	10.34%	3.61%
Industry 2				8.10%	11.90%	11.00%
Industry 3				8.15%	12.23%	3.41%
Industry 4				11.92%	8.69%	3.85%
Industry 5				10.15%	9.12%	3.63%

CHAPTER 5

SUMMARY AND CONCLUSION

In this paper, we test the accuracy of analysts from a new perspective using a market microstructure model introduced by Easley et al. (2002). Using intraday market data and a trade classification algorithm given by Lee and Ready (1991), we estimate the probability of a private information event occurring each day, the probability the event being bad news or good news, and the arrival rates of different traders (uninformed buyers, uninformed sellers, and informed traders) using maximum likelihood estimation. By comparing these estimates on days with and without recommendation changes, we find that changes in financial analyst recommendations do not correspond with a change in the probability of a private information event each day. The timing of the change in recommendations is sometimes consistent with the underlying change of the probability of news, but sometimes it is not, suggesting that financial analysts do not always make accurate recommendations. Even though they are inaccurate most of the time, uninformed investors generally believe financial analysts most of the time, although they sometimes choose not to believe them. Unfortunately they do this at the most inopportune times, choosing to believe when analysts are most often wrong, and choosing not to believe on the rare occasion when the analysts are right on average. These findings are robust when we use two-day recommendation period by incorporating both the day analysts change their recommendations and the day before the recommendation periods.

Furthermore, in light of this we suspect it is possible that a specialist might believe that orders in the opposite direction of analysts' recommendations on recommendation days are more likely to be information-based trades, thus giving different conditional probabilities depending on the existence and direction of a recommendation change. To test for this possibility, we develop a new index on the conditional probability of information-based trading and name the probability of information-based trade conditioned on sell and buy orders as PIN|sell and PIN|buy respectively. We examine whether there is any change on recommendation days with the probability of information-based trade (PIN), PIN|sell and PIN|buy, but we did not find any significant differences. This indicates that although we may observe a higher arrival rate of information traders on recommendation days, the probabilities of information-based trading does not change. More informed traders come to the market merely because the higher arrival rate of uninformed traders on recommendation days gives them a good opportunity to camouflage their trading effectively. If this is the case, the specialists, quite likely, would not set bid and ask prices any differently on those days. This excludes the possibility that the observed inefficiency of pricing to analysts' recommendation is due to the different behaviour of specialists when setting up their bid and ask quotes. The finding of indifference of specialists is further supported by our finding that the equivalence of the arrival rates of uninformed buyers and uninformed sellers remains in the no-recommendation period and both recommendation periods. This goes along with the common assumption in previous literature of the symmetry of uninformed buys and sells.

We try to find out whether the probability of informed trading we estimated has any relationship with the firm size, the trading volume, the volatility of daily return and the industry of the firm. However we don't find any coefficient significant. A more detailed study may be warranted, but this waits for future study.

One of the limitations of this thesis is that we cannot include all the available firms into our sample due to the sparseness of recommendation changes as the number of sample firms increases. This is especially problematic since most of our findings were of a negative nature where we were unable to reject certain restrictions. This makes our conclusion heavily dependent on the power of our statistical tests, which is compromised by having such a small sample. Even so, because of the wide diversity of firm sizes and industries, we still feel confident in generalizing our findings. Further tests with a larger sample dataset and longer time series may warrant future research.

Also, in this study the average of all the analysts' recommendations available in each day is used. However the quality of their recommendations may vary a lot from analyst to analyst. Keeping track of individual analysts may give us different results on the accuracy of their recommendations. However this may limit the sample size even more through both the number of firms and the number of days in recommendation periods. This may also warrant additional research.

Appendix

Appendix 1

The change of each parameter in the 2-day recommendation period

Ticker	In the up-recommendation period							In the down-recommendation period						
	α	δ	$\gamma = \alpha^*\delta$	$\beta = \alpha^*(1–\delta)$	ε_b	ε_s	μ	α	δ	$\gamma = \alpha^*\delta$	$\beta = \alpha^*(1–\delta)$	ε_b	ε_s	μ
AOL/TWX	* +	** +	** +	** –	** +	** –	** +	+	* –	* –	+	** –	** +	** +
APC	+	** +	+	–	** +	–	** –	–	–	–	+	* –	** +	** +
AT	* +	–	–	** +	–	** +	** –	+	–	–	+	* –	** +	** +
AWE	+	–	+	+	** +	** +	–	+	–	+	+	** +	** +	** +
BP	–	** +	** +	–	** +	** –	** –	+	–	–	+	+	** +	** –
BR	–	–	–	–	** +	–	+	+	–	–	+	** –	** +	** +
BSX	* –	** +	** +	** –	** +	** +	** +	–	–	–	–	** +	** +	** +
CC	+	–	–	+	** +	** +	** +	+	–	–	+	–	** +	** +
COF	–	+	+	–	** +	** +	** +	+	+	+	+	** +	** +	** +
DNA	–	* +	–	* –	** +	** +	** +	–	** –	** –	+	** +	** +	** +
DVN	–	–	–	+	+	** +	+	+	+	* +	–	** +	** +	** –
EDS	+	–	–	+	** +	** +	** +	–	–	–	+	** +	** +	** +
EOG	+	** –	** –	* +	** –	** +	** +	+	** +	** +	–	** +	** +	–
GDT	+	+	+	–	** +	–	** +	–	** –	** –	+	+	** +	** +
GPS	–	–	–	–	** +	** +	** +	–	–	–	–	** +	** +	** +
JBL	–	–	–	–	–	** +	** +	–	+	+	–	* +	* –	* –
LU	–	–	–	+	** +	–	+	+	+	+	–	** +	–	** –
MOT	+	** –	* –	+	** –	** +	** +	–	–	–	+	** +	** +	** –
MRK	+	** +	** +	** –	** +	–	** +	+	+	+	–	** +	** +	+
NOK	–	+	+	–	** +	+	** +	+	–	–	+	** –	** +	** +

Appendix 1 (cont'd)

The change of each parameter in the 2-day recommendation period

Ticker	In the up-recommendation period							In the down-recommendation period						
	α	δ	$\gamma = \alpha^*\delta$	$\beta = \alpha^*(1-\delta)$	ε_b	ε_s	μ	α	δ	$\gamma = \alpha^*\delta$	$\beta = \alpha^*(1-\delta)$	ε_b	ε_s	μ
PCS	–	* –	* –	–	** +	** +	** +	–	–	–	+	** +	** +	** +
Q	–	–	–	+	** +	** +	** +	+	–	–	* +	–	** +	** +
RD	–	** +	** +	** –	** +	** –	** +	+	–	–	+	** +	** +	** +
RIG	+	** –	** –	** +	** –	** +	** +	+	** –	** –	** +	** –	** +	** +
SAP	+	–	–	* +	–	** +	** +	–	** +	* +	–	** +	+	–
SBC	+	* +	* +	–	** +	** –	** –	–	** –	** –	** +	–	** +	+
SGP	+	–	–	+	** +	** +	** +	* –	+	–	–	** +	** +	** +
SLR	–	** +	+	** –	** +	** –	** +	+	+	+	+	** –	** +	–
T	+	** +	** +	–	** +	** –	** –	–	+	+	–	** +	** +	** –
VZ	+	* +	* +	–	** +	** +	+	+	** +	** +	* –	** +	** +	** –
Significant increase	2	11	8	4	23**	18	20*	0	3	4	3	19*	27**	18
Significant decrease	1	4	4	6	3	6	5	1	5	5	1	6	1	7
Insignificant change	27**	15	18	20	4	6	5	29**	22**	21**	26**	5	2	5

* means significant at 5% and ** means significant at 1%.

Appendix 2

The change of probabilities in the 2-day recommendation period

Ticker	Up- vs. no-recommendation period						Down- vs. no-recommendation period					
	Δ PIN		Δ PIN/sell		Δ PIN/buy		Δ PIN		Δ PIN/sell		Δ PIN/buy	
AOL'	3.5%	+	13.3%	+	–5.6%	–	6.2%	+	–5.3%	–	16.6%	+
APC	–2.9%	–	2.6%	+	–7.5%	–	1.4%	+	–1.5%	–	3.4%	+
AT	7.8%	+	–0.3%	–	14.5%	+	7.8%	+	–0.3%	–	13.9%	+
AWE	0.3%	+	0.5%	+	0.0%	+	2.9%	+	6.3%	+	0.0%	+
BP	–6.1%	–	4.6%	+	–15.4%	–	–1.7%	–	0.9%	+	–3.8%	–
BR	–4.2%	–	–0.1%	–	–6.8%	–	0.3%	+	4.2%	+	–3.2%	–
BSX	–8.3%	–	2.0%	+	–16.2%	–	–4.4%	–	0.3%	+	–8.3%	–
CC	0.7%	+	–0.7%	–	2.3%	+	2.5%	+	–0.7%	–	6.0%	+
COF	3.0%	+	0.0%	–	5.7%	+	–3.6%	–	0.0%	+	–6.1%	–
DNA	2.5%	+	–6.7%	–	9.6%	+	2.4%	+	–3.6%	–	7.1%	+
DVN	3.2%	+	–7.4%	–	11.9%	+	1.1%	+	–1.3%	–	3.0%	+
EDS	1.6%	+	–3.9%	–	6.5%	+	4.3%	+	–3.9%	–	11.3%	+
EOG	2.1%	+	–5.7%	–	9.2%	+	0.0%	–	5.9%	+	–4.5%	–
GDT	2.0%	+	3.1%	+	–0.3%	–	2.9%	+	–5.2%	–	10.5%	+
GPS	–2.5%	–	1.3%	+	–5.1%	–	–0.2%	–	0.6%	+	–1.2%	–
JBL	–0.3%	–	–1.3%	–	0.5%	+	–0.2%	–	2.9%	+	–2.7%	–
LU	–1.8%	–	–0.2%	–	–3.0%	–	0.3%	+	0.8%	+	–0.5%	–
MOT	3.8%	+	–2.5%	–	9.9%	+	–1.0%	–	6.8%	+	–7.9%	–
MRK	4.7%	+	16.0%	+	–5.9%	–	1.4%	+	9.8%	+	–5.9%	–
NOK	–0.7%	–	1.5%	+	–2.9%	–	–1.3%	–	0.5%	+	–3.0%	–
PCS	–2.2%	–	–2.2%	–	–1.8%	–	–3.4%	–	–1.3%	–	–4.2%	–
Q	–0.6%	–	–0.6%	–	–0.8%	–	1.2%	+	–3.1%	–	5.0%	+
RD	–2.5%	–	2.0%	+	–6.7%	–	–2.6%	–	0.2%	+	–5.2%	–
RIG	–0.6%	–	–14.2%	–	11.2%	+	–3.2%	–	–8.9%	–	2.1%	+
SAP	4.3%	+	–1.6%	–	8.3%	+	–1.9%	–	3.8%	+	–6.4%	–
SBC	–0.7%	–	–2.9%	–	1.7%	+	–1.8%	–	–7.0%	–	3.5%	+
SGP	–1.7%	–	–0.2%	–	–3.1%	–	2.0%	+	–1.7%	–	5.5%	+
SLR	–1.5%	–	0.8%	+	–3.3%	–	3.1%	+	–0.5%	–	5.8%	+
T	1.4%	+	8.4%	+	–6.2%	–	–0.6%	–	–1.2%	–	0.1%	+
VZ	1.0%	+	12.7%	+	–9.4%	–	0.3%	+	11.4%	+	–9.0%	–
Mean	0.0017		0.0060		–0.0030		0.0047		0.0030		0.0072	
St. Dev	0.0336		0.0610		0.0790		0.0284		0.0462		0.0679	
p-value	(0.5204)		(0.5392)		(0.4851)		(0.5653)		(0.5259)		(0.5424)	

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