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ESSAYS ON LIQUIDITY, TRADERS' STRATEGIES AND THE USEFULNESS OF ACCOUNTING INFORMATION

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Organization of the thesis

PART 1 (ORDER AGGRESSIVENESS AS A METRIC TO ASSESS THE USEFULNESS OF ACCOUNTING INFORMATION) – The first part of the thesis is devoted to a methodological contribution to the research on the usefulness of accounting information and to a review of the related literature. Motivated by the availability of high frequency data on orders and transactions, I propose to use traders' strategies, measured by order aggressiveness, as a metric to evaluate if market participants perceive accounting information as useful. I first present two critical surveys: on the literature on the usefulness of accounting information, and on the empirical research on the determinants of order aggressiveness. Finally, I report the results of an application of the decision usefulness metric proposed employing data from the Italian Stock Exchange.

PART 2 (*MARKET MAKERS AS INFORMATION PROVIDERS: EVIDENCE FROM STAR)* – The second part of the thesis presents an empirical investigation of the role of specialists interacting with a limit order book. I examine the effect of the introduction of specialists with information disclosure requirements in STAR, a segment of the Italian Stock Exchange dedicated to small-medium firms. I focus on the effect of these information disclosure obligations on market quality and on information asymmetries. This work contributes to the literature on the design of hybrid markets and to the literature on the economic consequences of information disclosure.

Contents

PART 1

ORDER AGGRESSIVENESS AS A METRIC TO ASSESS THE USEFULNESS OF ACCOUNTING INFORMATION

This part of the thesis aims to provide a methodological contribution to the literature on the usefulness of accounting information. Motivated by the availability of high frequency data on orders, quotes and transactions, I propose to use traders' strategies, measured in terms of order aggressiveness, as a metric to evaluate if accounting information is perceive as useful by market participants. In chapters 1 and 2, I present critical surveys of the literature on the usefulness of accounting information and on the empirical research on the determinants of order aggressiveness. The surveys define an interpretation framework of the field of work, review the most influential contributions and identify open questions. Finally, in chapter 3, I present an empirical application of the decision usefulness metric proposed. I test, through an analysis of order aggressiveness, whether earnings announcements of firms listed on the Italian Stock Exchange limit order book have information content. Consistent with microstructure models on the choice between limit and market orders, I find that order aggressiveness increases with the absolute value of unexpected earnings. The results provide evidence on the extent to which the information contained in earnings is used by traders.

INTRODUCTION

The vast body of literature on decision usefulness of accounting information examines the market response to the disclosure of financial statements items (recent critical surveys are contained in Fields et al. (2001) and Kothari (2001)). Most contributions, drawing their foundations in the seminal works of Ball and Brown (1968) and Beaver (1968), analyze the reaction of stock prices and trading volume. A group of works also compares price-based metrics and volume-based metrics as methods to test the market response (examples of which are Rohrbach and Chandra (1989), Cready and Ramanan (1991 and 1995), Cready and Hurtt (2002)). The availability of high frequency data on orders and transactions makes it possible to enrich the results of this branch of research. Accordingly, I here propose to use order aggressiveness as a complementary metric to evaluate the usefulness of accounting information. Ranking orders according to aggressiveness is a classification, first introduced by Biais et al. (1995), used by a number of empirical studies examining the order flow. Stock prices and trading volume are determined by order submission strategies, which are described by the aggressiveness classification. Thus, order aggressiveness provides a metric of the market reaction to information more primitive than measures based on stock prices and trading volume. Further advantages exist in the method I propose with respect to the traditional metrics: the effect of unfilled orders is taken into account, an intraday dataset can be exploited, and results can be segmented by characteristics of orders (therefore by categories of traders). As pointed out by Lev (1989), the traditional approach to evaluate decision usefulness maintains that when individuals act as if they use information, then such information can be considered useful. Following this approach, I suggest that analyzing order submission strategies provides evidence on the extent to which accounting information is useful for market participants. Different actors can be motivated to understand whether accounting information is found to be useful through an analysis of order aggressiveness. As implied by many works in this literature, accountants are interested in understanding how market participants perceive the information they

release, and standard setters are interested in investigating if accounting methods are appropriate to convey information. Moreover, the observation of traders' reactions helps investors to revise their evaluation of the stocks and to better estimate trading costs.

This work studies the usefulness of earnings announcements of firms listed on the Italian Stock Exchange limit order book by examining the reaction of order aggressiveness to unexpected earnings. I estimate an ordered probit that relates order aggressiveness to the absolute value of unexpected earnings and to the main market determinants of aggressiveness identified by previous literature (the bid-ask spread, the depth of the order book and price volatility). In line with the predictions of microstructure models on the choice between market and limit orders, I find that aggressiveness of both buy and sell orders increases with the absolute value of unexpected earnings. I interpret the existence of this relation as evidence that traders actually use the information contained in earnings. Consistently, abnormal trading volume and abnormal volatility signal a market reaction to the information disclosure. Nevertheless, when examining abnormal returns, a clear indication that market behavior is affected by earnings announcements does not emerge. The analysis presents an empirical application of the metric I propose and it aimes to provide a methodological contribuition to the decision usefulness research. The research design can be employed with data from the other exchanges to test different forms of information disclosures.

To my knowledge, no other contributions exist on the effect of unexpected earnings on the order flow. This work is thus related to the branch of studies that indirectly examine the effect of earnings announcements on traders' strategies by analyzing how earnings announcements affect market liquidity. Liquidity, generally measured by the bid-ask spread and the depth of the order book, is assumed to decrease in adverse selection costs determined by asymmetric information. In the theoretical literature there is no dominant view on whether earnings announcements represent a substitute (as in Kim and Verrecchia (1991), Demsky and Feltham (1994), McNichols and Truman (1994)) or a complement (as in Kim and Verrecchia (1994) and Livne (2000)) of private

information: in the former case, asymmetric information and adverse selection costs are expected to decrease after the announcements; in the latter case, asymmetric information and adverse selection costs are expected to increase after the announcements. Most empirical studies (for example Lee et al. (1993), Krinsky and Lee (1996), Libby et al. (2002) and Pronk (2006)) find that liquidity decreases in the period around earnings announcements. Fewer works (for example Morse and Ushman (1983), Venkatesh and Chiang (1986) and Skinner (1991)) document that earnings announcements do not significantly affect liquidity. The main difference from this field of research is that, instead of comparing market behavior in periods around earnings announcements and in neutral periods, I concentrate on the effect of unexpected earnings.

This analysis is also related to the empirical market microstructure literature on order aggressiveness. The first contribution in this field is provided by Biais et al. (1995) within an analysis of the interaction between the order book and the order flow. Griffiths et al. (2000) introduce the ordered probit method to study the determinants of order aggressiveness and inquire into the costs associated with order submission strategies and the information content of aggressive orders. Other works use different models with ordinal outcomes as dependent variables: Ellul et al. (2003) estimate a multinomial logit, Lo and Sapp (2005) estimate a symultanaeous equations model with an ordered probit for the type and the price of the order, and a censored regression for the size. Autoregressive models have also been proposed: Al-Suhibani and Kryzanowski (2000) use a VAR model, Bisière and Kamionka (2000) use an autoregressive conditional duration model. Degryse et al. (2005) study the impact of aggressive orders on the resiliency of the book. Ordered probit models have also been used by Ranaldo (2004) and Beber and Caglio (2006). Among these works, Beber and Caglio (2006)' is the most closely related to the present analysis since it tests whether order aggressiveness is influenced by information asymmetry in the period prior to earnings announcements. My approach differs from theirs because I focus on the period after the earnings

announcement and I directly estimate the relation between unexpected earnings and order aggressiveness.

This work is organized in three chapters: chapter 1 presents a survey of the literature on decision usefulness of accounting information; chapter 2 presents a survey of the empirical research on the determinants of order aggressiveness; chapter 3 describes an application of order aggressiveness as a metric of decision usefulness.

CHAPTER 1 – A SURVEY OF EMPIRICAL RESEARCH ON THE USEFULNESS OF ACCOUNTING INFORMATION

1. Empirical research on the usefulness of accounting information: motivation

The FASB's Conceptual Framework is an attempt to provide a metatheoretical structure for financial accounting (Wolk et al., 2001). It consists of six Statements of Financial Accounting Concepts (SFACS), which articulate the FASB's objectives and criteria to guide standard setters. The Conceptual Framework is formulated in broad terms and it is not context-specific; it has often been claimed that the literature on decision usefulness of accounting information is aimed at operationalizing the FASB's stated criteria of relevance and reliability for having decision usefulness of accounting information. The operationalization of analogous criteria stated by the IASB can also be imagined as a motivation for research after the introduction of the IAS.

In particular, SFAC n. 1 and n. 2 are important in this field of research. SFAC n.1 is concerned with the objectives of business financial reporting. It states that a common core characteristic of all outside users is their interest in the prediction of amounts, timing and uncertainties of future cash flows. SFAC n. 2 is devoted to the qualitative characteristics of accounting information and it is centered on relevance and reliability. The statement indicates that the primary criterion of choice between two alternative accounting methods involves asking which method produces the better, that is, the most useful, information. The document states that accounting information, in order to be useful for decisions, must have the qualities of relevance[1] and reliability[2].

[1] An accounting amount is defined as relevant if "it is capable of making a difference in a decision by helping users to form predictions about the outcomes of past, present and future events or to confirm or correct expectation". Relevance, thus, has three main aspects: predictive value, feedback value and timeliness. Predictive value refers to usefulness for predictions, such as cash flows for earnings power. Feedback value concerns "confirming or correcting decision makers' earlier expectations". Timeliness means that information is "available to decision makers before it loses its capacity to influence decisions".

[2] An accounting amount is said to be reliable if it represents what it purports to represent. Reliability, in turn, is composed of three parts: verifiability, representational faithfulness and neutrality. Verifiability refers to the degree of consensus among measurers. Representational faithfulness refers to the idea tha the measurement itself should correspond with the phenomenon it is attempting to measure. Neutrality deals with the belief that the policy-setting

As noticed by Lev (1989), the traditional approach to examining the usefulness of accounting information maintains that when individuals act as if they use information, then such information can be considered useful. The literature concentrates on how markets react to the release of accounting information and, in particular, earnings. The association between accounting variables and stock prices is considered as evidence of usefulness of the release of the corporate news. Lambert (1997) points out that empirical research fouses on market reactions because stock prices "represent the aggregation of individual investors' valuations of the firm and the information upon which that valuation is based". Since stock market prices incorporate more information than that available to any single investor, no investor likely has all the information that is incorporated in prices. Starting from the 1990s, most of papers investigating the association between accounting numbers and market prices, use the term "value relevance" instead of "usefulness" of accounting information to define the purpose of their analyses. I talk of usefulness of information because it is a broader concept than value relevance and it encompasses works that consider measures of market reaction to news releases not directly related to prices.

Three main theoretical frameworks have been used to justify the relation between market behavior and accounting information. Firstly, Gordon (1962)'s model posits that the value of the firm to shareholders is the present value of expected future dividends to be received by shareholders. Secondly, the model of Miller and Modigliani (1961) show that the value of the firm can be equivalently modeled as the present value of cash flows from operations minus cash investment in assets. Finally, Ohlson (1995) and Feltham and Ohlson (1995), who base their clean surplus theory on the residual income model, show that under certain conditions share price can be expressed as a weighted average of book value and earnings.

Empirical research on the usefulness of accounting information started in the late 1960s with the seminal papers by Ball and Brown (1968) and Beaver (1968). The earlier works are concerned,

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process should be primarily concerned with the relevance and reliability rather than the effect a standard or rule might have on a specific user group or the entreprise itself.

above all, with the extent to which earnings are useful to predict stock price movements. The evidence on this issue shows that earnings can explain no more than 10% of stock returns variability; this is consistent with investor surveys, according to which more timely information than earnings play a more important role for investment decisions. Other works test the usefulness of specific accounting amounts different from earnings and others compare the predictions of theoretical models of valuation to the relevance of information. Some of more recent papers examine the usefulness of earnings as predictors of stock prices over time. The results of most of these studies show that the explanatory power of the relation between earnings and stock prices is declining. This reflects a widespread impression, both in the domain of academics and of practitioners, that accounting has not kept up with wholesales changes in the economy. It is often claimed that a high-tech, service-oriented economy has rendered traditional financial statements less useful for assessing shareholder value.

An important issue is the potential interest of non-academic constituents in the results of the research on the usefulness of accounting information. It is generally assumed that the findings of these studies are relevant for accountants because they help them to better understand how markets perceive the aggregate information contained in earnings and the specific information associated to single items. More frequently, papers claim that standard setters are the main non-academic constituents that should be interested in the market reaction to the release of accounting information. The argument behind this is that, consistently with prescriptions of the FASB, this field of research allows standard setters to evaluate whether accounting rules appropriately convey information. Holthausen and Watts (2001) criticize this view by saying that it is not verified that standard setters consider the association returns-prices desirable since the primary role of accounting should not be equity valuation. They conclude that research on value relevance of accounting information is not descriptive and it provides little insight for standard setters. This criticism is too extreme and, as remarked by Barth et al. (2001), even if results on the relation

between accounting numbers and market behavior are neither necessary nor sufficient for standard setting, this does not diminish their relevance to standard setters.

In the remainder of this chapter I describe the main results of the empirical literature. The literature is remarkably vast and this survey is limited to examples of the most influential contributions. In section 2 I focus on the determinants of the usefulness of accounting information and, in particular, of earnings (Table 1 summarizes the major determinants of the usefulness of earnings); in section 3 I consider other open questions on the market reaction to the release of earnings; in section 4 I concentrate on methodological issues.

2. The determinants of the usefulness of earnings

Investment in intangibles

The increasing degree of intangibility of assets has often been related to the decreasing relevance of earnings. An influential contribution is provided by Amir and Lev (1996), who observe that financial accounting information is of limited value to investors when valuing firms in the intangible-intensive cellular phone industry because current accounting rules only record intangible assets in limited circumstances. Instances of other works claiming that the value relevance of accounting information is decreasing in intangible intensity are Elliott and Jacobsen (1991), Jenkins (1994), Lev and Zarowin (1999). It is worthwhile mentioning the different approach taken by Dontoh et al. (2006), who show that non-information based trading activity is higher for growth firms than for value firms. They measure information based trading activity by regressing the trading volume on the moments of the distribution of analysts' forecasts revisions[3]. Their results support the conjecture that non-information based trading is responsible for a part of the decline in the explanatory power of the price/earnings relation.

[3] The analysis is motivated by the theoretical predictions of the Noisy Rational Expectations Equilibrium model in Dontoh et al. (2004).

Accounting conservatism

Differences in accounting conservatism[4] can influence in a different way the response of investors to the release of information. Hayn (1995) documents that firms reporting negative earnings have smaller earnings response coefficients than firms reporting positive earnings. She also presents evidence that the frequency with which firms report negative earnings has increased over time. Basu (1997)[5] conjectures that accounting conservatism lead earnings declines to be much more transitory than earnings increases. He finds that the degree of conservatism has increased in recent years. Hayn's and Basu's results suggest that the increase in the frequency of negative earnings over time could contribute to the decline in the incremental value relevance of earnings. Givoly and Hayn (2000) show that, since the early 1970s, the association between contemporaneous returns and earnings is stronger when returns are negative than when they are positive, reflecting increasing accounting conservatism attributable at least in part to increasing legal liability. Finally, in the framework of an international comparison, Black and White (2003), find support for the hypothesis that conservatism reduces the value relevance of earnings relative to book value and dividends.

Persistence of earnings

The persistence of earnings should positively affect their usefulness to investors and, as a consequence, a higher response to the release of more persistent earnings is expected. It is reasonable to believe that the different components of earnings are characterized by a different persistence. Methodological problems arise in case of the existence of transitory earnings when returns are regressed on earnings. In fact, as observed by Kothari (2001)[6], the coefficients on total

[4] In SFAC n. 2 conservatism is defined as "a prudent reaction to uncertainty to try to ensure that uncertainty and risks inherent in business situations are adequately considered".

[5] In this study deflated earnings are regressed on stock returns and for a dummy signaling negative returns; this allows allows to investigate the timeliness of accounting information. The approach has been used by other works, for example Givoly and Hayn (2000), examining conservatism.

[6] Kothari (2001) presents a simple example. Reported earnings are: $X_t = x_t + u_t$, where x_t is the permanent component and follows a random walk, and u_t is the transitory component and follows a white noise process. The innovation in the random walk is not correlated with the transitory component. The market sensitivity to the transitory component is

earnings and the explanatory power of the regression are biased downward because the model does not directly relate permanent earnings to returns.

One of the first studies on this issue is conducted by Beaver and Morse (1978), who find evidence that investors perceive that a portion of earnings consists of a transitory component. They point out that if the transitory component of earnings does not contribute to influence stock prices, there exists a negative correlation between price-earnings ratios and earnings growth in the same year and a positive correlation between price-earnings ratios and earnings growth in the following year. In fact, they find that stocks which have high price-earnings ratios at the end of a year have experienced low earnings growth in that year and high earnings growth in the subsequent year. Similarly, low price-earnings ratios stocks experience high growth in the year just ended and low growth in the subsequent year.

More recent results confirm the importance of the persistence of earnings: Kormendi and Lipe (1987) find evidence that the persistence of earnings increases earnings response coefficients; Elliott and Hannah (1996) show that firms have become increasingly likely to report negative earnings and nonrecurring items; Barth et al. (1999) find that firms with patterns of increasing earnings in the previous years display higher stock price responses to the release of earnings news; since, as previously documented for example by Hayn (1995), the persistence of earnings is increasing in the size, Collins et al. (1997) claim that the increase in the proportion of small firms in the Compustat sample might be a reason for the alleged decline in the value relevance of earnings; Ou and Sepe (2002) use the spread between current earnings and one-year ahead consensus in analysts' forecasts as a proxy for the transitory component of earnings and observe that the value relevance of current earnings is decreasing in this measure.

1, whereas the sensitivity to the permanent component is $\beta = (1+1/r)$. The typical returns-earnings regression is: $R_t = \gamma_0 + \gamma_1 X_t / P_t + z_t$. It follows that the coefficient of earnings lies between 1 and β, because X_t is the sum of variables that have different slope coefficients relating them to the dependent variable.

Timeliness of earnings

A number of studies, for example Kothari and Sloan (1992) and Beaver and Ryan (1993), show that annual returns predict future earnings for at least three subsequent years. This suggests that earnings reflect news with a lag relative to stock prices.

Collins et al. (1994) argue that earnings' lack of timeliness partially explains the low explanatory power of earnings with respect to stock returns. They maintain that the delay in accounting numbers is partly due to the tendency to delay recognition of expected future benefits from current cash expenditures recognized currently as expenses. It is claimed that the emphasis on historical-cost measurement and transaction-based accounting leads the conventional accrual model to "often trade off timeliness in recognizing changes in net asset values in favor of objectivity, verifiability, and/or conservatism". To control for the anticipated component of current earnings, Collins et al. include lagged earnings yield as a proxy for expected current earnings growth. To approximate the revisions in the market's expectations taking place over a year, they simultaneously include the realized future earnings growth rates and future returns in the return-earnings model[7]. In fact, the role of future returns is to control for the surprise components embedded in the future periods' earnings growth rates, which are irrelevant in explaining the current period's returns. The results show that by adding these regressors the explanatory power of the relation increases dramatically.

Ryan and Zarowin (2003) hypothesize that the decrease in the contemporaneous linear returns-earnings association is due to the fact that earnings increasingly reflect news with a lag relative to stock prices and to the increasing asymmetry with which earnings reflect good and bad news. They find support for their hypotheses by regressing annual earnings on current and three lagged annual price changes, with dummy intercept and slope coefficients for negative price changes. The equation captures earnings' association with price changes at up to three-year lag, and it allows the

responsiveness of earnings to current and lagged price changes to depend on the signs of price changes.

Business change

Lev and Zarowin (1999) argue that the deterioration in the usefulness of accounting information can be due to business change not adequately reflected by the current reporting system. They document the pattern of business change by ranking the firms in their sample on book value and market value and by observing switches from the original segmentation. They find that higher levels of business change are associated with lower relevance of earnings, measured by earnings response coefficients and explanatory power of the returns-earnings regression. They also show that an increase in R&D intensity is associated with a decline in earnings informativeness and that an increase in the rate of business change is associated with an increase in R&D intensity. This suggests that, among other drivers, innovation, generally brought about by investment in R&D, is an important factor in the declining usefulness of accounting information. They conclude by stating two proposals aimed at enhancing the usefulness of accounting information when coping with business change: the capitalization of intangibles and the systematic restatement of financial reports.

Quality of accounting information

The quality of earnings is likely to affect the perceived usefulness of accounting information if the objective of accounting is considered to be "the prediction of future investor cash flows or stock returns" (Lev, 1989).

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[7] The model, used also by other papers, is: $R_t = \beta_0 + \beta_1 UX_t + \sum_{k=1}^{3} \beta_{k+1} \Delta E_t (X_{t+k}) + e_t$, where R_t is the return, X_t is the growth rate of earnings, UX_t is the unanticipated earnings growth rate, and ΔE_t is the revision in market expectations.

Lev and Thiagarajan (1993) measure earnings quality by using 12 "fundamentals" identified by financial analysts in evaluating earnings quality[8]. They find that the higher is the earnings quality the higher are earnings response coefficients.

In a series of empirical papers (for example, the previously cited Lev (1989), Lev and Zarowin (1999), Baruch Lev argues that GAAP have to be revised because they produce low quality earnings that exhibit weak correlation with stock returns. This argument is closely related to the lack of timeliness in earnings, i.e. earnings can be predicted by previous stock returns.

Interest rates

Macroeconomic changes have also been analyzed as determinants of changes in the usefulness of earnings, for example by Lev (1989) and Ball et al. (1993). In particular, Collins and Kothari (1989) examine the role of interest rates. They maintain that if the risk free rate of interest rises, then, ceteris paribus, the discounted present value of the revisions in expectations of future earnings innovations falls, inducing a negative temporal association between interest rate levels and earnings response coefficients.

Firm-specific variables

RISK – How risk is related to earnings response coefficients is a controversial issue. Collins and Kothari (1989) and Easton and Zmijewski (1989) find lower earnings response coefficients for stocks with higher betas, conventionally used as a proxy for systematic risk, and they explain this result by conjecturing that higher risk reduces the demand for the stock at the arrival of the news. Conversely, Cready et al. (2000) find a significantly positive relation between systematic risk and earnings response coefficients, whereas Warfield et al. (1995) and Chambers et al. (2005) find no significant relation. Chambers et al. (2005) also find that total risk, measured by the variance of

[8] For each firm in the sample, a score of 1 or zero is assigned corresponding to each fundamental. Firms are then grouped according to the aggregate scores of earnings quality and earnings response coefficients are compared across

stock returns, is positively related to earnings response coefficients. They argue that the sensitivity of dividend expectations to news is increasing in idiosyncratic risk. Basu (2005) remarks that research design differences make it difficult to compare the contributions on the relation between risk and the market response to the release of accounting information.

CAPITAL STRUCTURE – Also the capital structure can influence the response of stock prices to earnings news. In fact, in high levered stocks, an increase in earnings adds strength and safety to bonds and other outstanding debt, so that much of the good news in earnings goes to the debtholders rather than to the shareholders. Consistently, Dhaliwal et al. (1991) find that more highly levered firms have lower earnings response coefficients. Dimitrov and Jain (2006) show that changes in financial leverage are associated to negative returns and they claim that changes in leverage are signals of the performance less noisy than earnings[9].

GROWTH OPPORTUNITIES – Growth opportunities have been often found, for example by Collins and Kothari (1989), to have a positive effect on earnings response coefficients[10].

INFORMATION NOT INCORPORATED IN EARNINGS – As Beaver (1998) points out, announcements of litigation, contract awards, petroleum discoveries, future capital expenditures, anticipated strikes are examples of events that may affect future earnings but may not be reflected in current earnings.

INFORMATION NOT INCORPORATED IN PRICES – Beaver (1998) identifies changes in earnings per share, which are not expected to alter the dividend-paying ability of the firm. Changes in depreciation methods and reliance on historical cost basis of accounting are two among many possible examples. A change in the accounting method for depreciation can produce a change in

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the different groups.

[9] The results are also consistent with the findings of the empirical works on the determinants of capital structure: see, for example the survey by Eckbo et al. (2006).

[10] The most used measure of growth opportunities is the market to book ratio. Since, starting from Fama and French (1993), the market to book ratio has been identified as a risk factor, it could be interesting to examine the relation between growth opportunities and risk and examine the consequences on earnings response coefficients.

earnings that is permanent in the sense that the level of earnings is expected to be permanently affected, but it may not be an event that alters the firm's dividend-paying ability.

3. Further questions on the determinants of the usefulness of accounting information

Usefulness of earnings vs book value and dividends

A number of papers investigate the usefulness of earnings relative to the usefulness of book value and dividends. This also allows to explore the time-varying relevance of information.

Bernard (1995) finds that a model relating market value to book value and earnings have higher explanatory power than a model relating market value to dividends alone. Burgstahler and Dichev (1997) find that the return-on-equity affects the relevance of earnings. Barth et al. (1998) show that for firms in financial distress, the value relevance of book value dominates that of earnings and, in general, the relevance of earnings is affected by the degree of unrecognized assets. Hand and Landsmann (2005) find that the information content of dividends is greatest when in presence of transitory earnings. Some articles, for example King and Langli (1998) and Arce and Mora (2002), also compare the value relevance of earnings and book values across different countries.

Brief and Zarowin (1999) compare the value relevance of book value and dividends versus book value and reported earnings. They regress market value on book value, earnings and dividends and they assess the information content of the explanatory variables by observing the R^2 of the regression. They find that book value and dividends have almost the identical explanatory power as book value and reported earnings. This contradicts the motivation for accrual accounting, which is based on the enhanced value relevance of accruals versus pure cash flows or dividends. They also segment the sample according to the persistence of earnings. The ratio of earnings per share divided by beginning of period share price is used to classify the sample into two permanent versus transitory earnings groups. For firms with transitory earnings, the results show that dividends have greater explanatory power than earnings, thus suggesting that dividends can be viewed as a

surrogate of permanent earnings. Finally, they replicate the analysis focusing only on firms in the pharmaceutical and chemical industries, which are known to have large amounts on unrecognized assets and for which, consequently, book value is a relatively poor indicator of value. They find that for these firms, when earnings are transitory, dividends have greater value relevance than both book value and earnings. The paper suggests the importance of the context in evaluating the information content of accounting information. Whether book value, earnings or dividends is the most important valuation signal depends on both the firm's overall characteristics and its performance in the particular period.

A stream of research suggests that the value relevance of earnings and book values move inversely to one another and that if the value relevance of earnings has decreased over time then the value relevance of book values should have increased. Jan and Ou (1995), Berger et al. (1996) find that book values take on increase importance relative to earnings when earnings are negative or contain nonrecurring items. They argue that on the one hand book values serve as a better proxy for future earnings when current earnings contain transitory components and, on the other hand, book values serve as a proxy for the abandonment option.

Collins et al. (1997) examine the value relevance of earnings and book values over time and find that, contrary to previous research in this area, the combined value relevance of earnings and book values has not declined. To assess the value relevance of accounting information they regress share price on earnings and book values and they decompose the explanatory power of the model following Easton (1985)'s method[11]. Precisely, they identify the incremental explanatory power of earnings, the incremental explanatory power of book values and the explanatory power common to both earnings and book values. They also find that intangible intensity, nonrecurring items, negative

[11] Following Theil (1971), three equations are estimated: $P_{it} = \alpha_0 + \alpha_1 E_{it} + \alpha_2 BV_{it} + \varepsilon_{it}$, $P_{it} = \beta_0 + \beta_1 E_{it} + \varepsilon_{it}$, $P_{it} = \gamma_0 + \gamma_1 BV_{it} + \varepsilon_{it}$; where P is the share price, E is earnings and BV is the book value. The incremental explantory power is given by the difference between the R^2 correspinding to the three models.

earnings and firm size explain the temporal shift in the relative importance of earnings and book value in valuation.

Francis and Schipper (1999) document that accounting information has not lost its relevance over the 1954-94 period by using two different methods. Firstly, they examine the market adjusted returns on hedge portfolios formed on the basis of the sign of the change in earnings, cash flows and other fundamental values. These returns are compared to the market-adjusted return to a perfect foresight returns-based hedge portfolio. They find that the returns to each of the hedge portfolios as a proportion of the perfect foresight returns-based portfolio are not decreasing over time. Secondly, following the standard approach in the literature, they analyze the explanatory power of three regressions: the first investigates the ability of earnings to explain market-adjusted returns; the second examines the ability of assets and liabilities to explain market values; and the third examines the ability of book values and earnings to explain market value of equities. The results show that the explanatory power of the first relation is decreasing over time whereas the explanatory power of the other two relations is increasing. When the analysis is also replicated separately for high-technology firms the results are analogous.

Components of earnings in the returns-earnings relation

The reaction to earnings can be decomposed into two components: the reaction to cash flows and the reaction to accruals. It is reasonable to believe that cash flows and accruals have different information content. As Bernstein (1993) argues, cash flows from operations, as a measure of performance, is less subject to distortion than is the net income, because the accrual system relies on a high degree of subjectivity. This is also consistent with the argument used by FASB (1980, para. 54) to emphasize the importance of cash flows in financial statements.

Bernard and Stoiber (1989) find that stock price responses to the release of information about the cash flows and accrual components of earnings are not systematically different and conclude that

trading strategies exploiting this inefficiencies can be devised. This is in line with what some financial analysts argue, namely that analyses of this type can be used to detect mispriced securities. A more detailed study on this issue is conducted by Sloan (1996). He first documents that the persistency of current earnings is decreasing in the magnitude of the accrual component of earnings and increasing in the magnitude of the cash flow component. He finds that the earnings expectations embedded in stock prices fail to fully reflect the higher persistence attributable to the cash flow component of earnings and the lower earnings persistence attributable to the accrual part. The results also show that there exists a profitable trading strategy that exploits the naive earnings expectations embedded in stock prices[12]. Finally, since the abnormal stock returns represent a delayed response to predictable changes in future earnings, they are concentrated around the earnings announcement under study. The accrual anomaly, i.e. the existence of a profitable trading strategy based on publicly available accruals, is explored by several papers, for example Xie (2001), Francis et al. (2003) and Desai et al. (2004).

Other papers compare market reactions to cash flows and accruals, for example Bowen et al. (1987), Dechow (1994), Black (1998). It is worthwhile to cite the work of Dechow et al. (1999), who develop a theoretical model whose main prediction is that earnings should have a higher correlation with stock prices than cash flows.

Analysts' forecasts and the usefulness of earnings

Starting from the seminal papers by Benston (1966) and Ball and Brown (1968), many studies indicate that much of the price reaction associated with earnings occurs prior to the announcement of earnings. It is interesting to investigate how sources of information alternative to corporate announcements, in particular analysts' forecasts, affect the response of investors to the release of earnings.

[12] A long position in firms reporting high levels of accruals relative to cash flows and a short position in firms reporting high levels of accruals relative to cash flows yield positive abnormal returns without considering transaction costs.

A branch of theoretical studies examines whether earnings announcements represent a substitute or a complement of private information: in the former case asymmetric information is expected to decrease after the announcements; in the latter case asymmetric information is expected to increase after the announcements. Kim and Verrecchia (1991) show that the expectation of imminent earnings news may stimulate some traders to search for information immediately prior to the announcement. Following this intuition, Demsky and Feltham (1994) and McNichols and Truman (1994) argue that, since the information acquired is incorporated into prices before the announcement, asymmetric information decreases after the announcement. On the other hand, Kim and Verrecchia (1994) claim that, because the information is noisy and certain traders have superior ability to process the news, information asymmetry should be higher after the release of information[13].

An interesting empirical contribution on this issue is the paper by Francis et al. (2002), who investigate whether analysts' reports reduce the usefulness of earnings announcements. They find a significant positive cross-sectional association between aggregate abnormal returns to analysts' reports and to earnings announcements. This relation is inconsistent with the prediction that analyst reports pre-empt earnings announcements. They also find that both mean and aggregate abnormal returns to earnings announcements increased significantly over 1986-1995. This is not necessarily inconsistent with prior research which reports that the value relevance of earnings, as measured by the ability of earnings to explain cross-sectional variation in long-window returns, has decreased over time. In fact, abnormal returns measure new information conveyed by earnings announcements while value relevance metrics measure the extent to which the earnings number summarizes information in the marketplace, from whatever source. They conclude that it is possible that investors' use of information which is not summarized by the bottom-line earnings number is

[13] These models also investigate the effect of information on liquidity. The relation between liquidity and information is determined by adverse selection costs, which in turn are increasing in asymmetric information. A different approach is taken by Bushman et al. (1997)', who prove that, even if private information is dissipated by the announcement, liquidity can decrease after the announcement due to the presence of discretionary liquidity traders.

increasing at a faster rate than their use of information which is summarized by earnings, while at the same time earnings announcements are increasingly bringing new information to the market.

Post-earnings announcement drift

Several studies focus on the post-earnings announcement drift, i.e. the tendency of markets to fully incorporate with a lag, generally of more than one month, the information after an earnings announcement[14].

Bernard and Thomas (1989) document drifts lasting up to 60 days. As noticed by Kothari (2001), a large fraction of the drift is concentrated in the three-day periods surrounding future quarterly earnings announcements, as opposed to exhibiting a gradually drifting abnormal return behavior.

The possibility that even professional investors do not understand the time-series properties of earnings has been considered. For example, several studies (e.g. Abarbanell and Bernard, 1992; Bradshaw et al. 2001) show that financial analysts, commonly viewed as sophisticated investors, do not fully incorporate the implications of current earnings for future earnings in their forecasts. Arbanell and Bushee (1997 and 1998) argue that financial analysts underreact to very fundamental signals stemming from securities which lead, in turn, to forecast error which, in turn, lead to incomplete security price adjustments. Brown and Han (2000) find that some firms exhibit first-order autoregressive properties and they argue that investors recognize this only for firms that have relatively higher pre-disclosure information.

Bartov et al. (2000) find that the proportion of firm shares held by institutional investors is negatively correlated with the observed post-announcement abnormal returns. If, as previous research suggests, institutional ownership is a proxy for investor sophistication, the findings suggest that unsophisticated investors determine the post-announcement drift. However, tests evaluating the validity of institutional holdings as a proxy for investor sophistication yield only mixed results.

[14] The existence of a post-earnings announcement drift represents a violation of the hypothesis of efficient markets. The issue is thus related to empirical literature examining the efficiency of markets.

Another possibility, as argued, for example, by Wyatt (1983), is that transaction costs are too high relative to the potential gain that can be earned from the mispricing of securities. The effect of size on the drift might be related to this explanation: Bhushan (1994) and Hew et al. (1996), among others, show that the effect appears to be more important for smaller firms than for larger ones.

Kothari (2001) argues that investor sophistication and transaction costs are unlikely to explain the drift, because these argument could not be explain the part of the drift found one-three quarters ahead earnings announcement days.

Garfinkel and Sokobin (2006) find that opinion divergence, measured by unexpected trading volume at the earnings announcement date, positively correlates with the future drift in returns. This is consistent with the model of Varian (1985), according to which opinion divergence lowers asset prices and can thus be considered as a risk factor. Examples of other explanations of the drift concerned with the omission of risk factors in the model used to compute abnormal returns are Ball (1992) and Kraft (1999).

Other studies explore how the drift is exploited by traders. Ke et al. (2003) examine trades of insiders subject to the filing requirements of section 16 of the SEC Act of 1934. They define a string as a sequence of consecutive quarters in which quarterly earnings are increasing and a break as the date in which the trend ends. Barth et al. (1999) and DeAngelo et al. (1996) show that breaks are associated with economically and statistically significant stock price drops. Insiders therefore have an incentive to sell stock in advance of breaks. Ke et al. find an increase in the frequency of net insider sales in the ninth through third quarters before the break for our sample firms. Not trading immediately before the break may reflect insiders' desire to avoid the appearance of exploiting inside information and the associated costs stemming from adverse publicity or litigation. Ke and Ramalingegowda (2005) find that institutional investors that actively trade to maximize short term profits trade to exploit the post earnings announcement drift. They also find that arbitrage

trades accelerate the speed that stock prices reflect the implications of current earnings for future earnings.

Foster et al. (1984) examine the possibility that the post-earnings announcement drift may derive from the earnings expectation model used by the researcher. They find strong evidence of the drift when measuring earnings surprise as the difference between quarterly earnings of the current year and of the previous year. With other proxies for unexpected earnings there appears to be no such drift.

Finally, the drift involves also the reaction to restatement announcements and only few works on this issue exist. A recent study examining this question is Palmrose et al. (2004), who examine different determinants of market reactions to restatement announcements.

4. Methodological issues

Focus on earnings

Most of the literature analyze market reaction to earnings announcements to assess the usefulness of accounting information. The results of the studies examining the association between financial ratios and stock prices (for example Freeman, 1983 and Lev, 1989) do not indicate a dominance of any financial ratio on earnings in terms of explanatory power of the empirical models.

Two main research designs can be identified: the former concentrates on the relation between price and book value, the latter examines the relation between returns and earnings[15]. Selection of which approach to use depends jointly on the hypotheses dictated by the research question and on econometric considerations (Landsman and Magliolo, 1988). When examining price levels the focus is on what is reflected in value, whereas when examining returns the focus is on what is reflected in changes of value.

Measures of unexpected earnings

Earlier studies, for example Ball and Brown (1968), Brown and Kennelly (1972), measure unexpected earnings by the seasonal difference in earnings. As the earnings announcement date approaches, investors revise their expectations about and such revisions affect stock prices. Accordingly, the seasonal difference in earnings, at the time of the announcement, might convey only a small part of the total information in earnings. Starting from Foster et al. (1984), several papers examine price reactions to standardized unexpected earnings, defined as the ratio between the seasonal difference in earnings and the standard deviation of the differences reported in previous quarters. Other recent contributions, for example Arbanell and Bernard (1992), Bartov et al. (2002) and Liang (2003), measure unexpected earnings by the difference between actual earnings and consensus in analysts' forecasts. On the other hand, the revision of future earnings' forecasts can also be considered. Liu and Thomas (2000), for example, by adding the revision of future earnings' forecasts in a regression relating unexpected returns and unexpected earnings, find that the explanatory power increases dramatically.

Time window

The choice of the time window over which to evaluate the market reaction to the news is crucial. Scott (1997) distinguishes causation studies, which consider a short time window and estimate the direct market reaction to the release of information, and association studies, which concentrate on long time periods and may thus be affected by confounding events. A narrow window might induce to understate the usefulness of information if price revisions continue beyond the period under analysis; a wide window, on the other hand, might determine an overstatement of the incremental contribution of the information released, as prices reflect other unrelated investors' reactions. Moreover, as remarked by Kothari and Warner (2006), in long horizon studies the appropriate

[15] Prices and book values are stock variables whereas returns and earnings are the corresponding flow variables. The results of the two approaches are equivalent under very restrictive assumptions, as remarked, for example, by Lo and

choice of the model for computing abnormal returns is particularly critical because small errors in risk adjustment can make an economically large difference. Alternatively to risk adjusted abnormal returns, two measures of abnormal performance are often used in works examining long time windows: (i) buy-and-hold abnormal returns (BHAR), first used by Ikenberry et al. (1995), are the returns obtained from a buy and hold strategy in excess with respect to the returns obtained from a comparable strategy using otherwise similar (usually in terms of risk) nonevent firms; (ii) following Jaffe (1974), the Jensen-alpha, i.e. the intercept from a multifactor model, is interpreted as the post-event abnormal performance of the event firms.

Computation of abnormal returns

The computation of abnormal returns can drive the results on the usefulness of accounting information. The market model and the Fama and French (1993)'s three-factor model are the most used methods to estimate abnormal returns, even if these models are known to explain a small part of the variance in stock returns. Kothari (2001) stresses the importance of taking into consideration changes of sensitivity to risk and identifying risk factors and sensitivity to risk. He points out that problems deriving from random errors in estimation of risk are mitigated if the study is conducted at a portfolio level; otherwise, if estimated abnormal returns are correlated to firm's specific variables, random errors weaken the correlation and thus the power of the test.

Deflators of price and earnings

When explaining the variance of market capitalization, prices are often deflated by the book value, which is considered as a summary of the factors and events that led to the current capitalization (Barth and Kallapur, 1996). Easton (1998) suggests to deflate prices by the previous year's book value, because it is less subject to managerial manipulations. An alternative approach is proposed by Easton and Harris (1991). They claim that book value and market value are both stock variables

Lys (2000).

indicating the wealth of the firm's shareholders. The related flow variables are, respectively, earnings divided by price at the beginning of the return period and market returns. Therefore, they argue that earnings divided by beginning of period price should be associated with stock returns. They find that abnormal returns are significantly related to earnings divided by beginning of period price and to earnings divided by the corresponding year price change both in univariate and multivariate regressions. Many papers written after this contribution deflate unexpected earnings by beginning of period price.

The effect of scale

Brown et al. (1999) is one of first methodological papers to show that operationalizing decision usefulness as R^2 from regressions of stock prices on earnings or book values of equity can be inappropriate[16]. In fact, the size of the stock is a scale factor conditioning the R^2. Scale is a multiplicative factor that affects the observed dependent and independent variables. When scale effects are large, ceteris paribus, one can expect the R^2 to be higher, because the scale factor contributes more variation to the observed variables relative to the amount contributed by the variables of interest. When scale effects are large enough, the researcher is essentially regressing the scale on itself, resulting in an R^2 that approaches unity. Thus, a difference in R^2 between two samples can arise from differential scale effects in the samples and not to a difference in explanatory power of the variables of interest. Brown et al. (1999) also show analytically that the R^2 is increasing in the coefficient of variation of the scale. They regress stock price on earnings and on book value of equity over the period 1958-1996. As Collins et al. (1997), who estimate the same regression over a slightly different time sample, they find that R^2 are increasing over time. However, when the coefficient of variation of the scale, proxied by the stock price and the book

[16] An interesting extension of the analysis is conducted by Lo (2004). He shows that deflating the data by a proxy for scale and including a scal proxy as independent variable can solve the problem. It must be noticed that in general the scale is unobservable.

value of equity, is taken into account, the R^2 are found to be decreasing over time. In an alternative approach to eliminate the effect of the scale, they also rerun the regression after deflating each observed variable for the scale, in this case proxied by the price of the stock one year earlier. They find that the R^2 are again decreasing over time, thus contradicting the results of Collins et al. (1997).

Lack of timeliness in earnings

If earnings reflect news with a lag relative to stock prices a problem of errors-in-variables and omitted correlated variables merge, which bias downward the earnings response coefficients and reduces the explanatory power of the return earnings regression[17]. Following Kothari (2001), empirical literature suggests possible solutions to the problem: (a) include future earnings in the return-earnings model as Jacobson and Aaker (1993) and Warfield and Wild (1992); (b) expand the return-earnings measurement window as Fama (1990); (c) include leading period return as Kothari and Sloan (1992) and Warfield and Wild (1992); (d) include both future earnings and future returns as Kothari and Shanken (1992), Collins et al. (1994); (e) use analysts' forecasts instead of future returns as Liu and Thomas (2000) and Dechow et al. (1999).

Intertemporal stability of the market reaction to accounting information

The usefulness of accounting information presupposes a certain degree of stability of market response over time. Among the others, Bowen et al. (1987) and Lev (1989) show high fluctuations of earnings response coefficients and explanatory power of the models over time. An interesting contribution on this issue is provided by Kothari and Shanken (2003) in the critique to Core et al. (2003). Core et al. (2003) examine whether equity valuation using financial variables in the New

[17] If prices lead earnings only a part of earnings is a surprise for investors and an endogeneity problem arises. For example, the model $P_{it} = \alpha_0 + \alpha_1 E_{it} + \varepsilon_{it}$ is estimated, but the symoultaneous relation $E_{it} = \alpha_0 + \alpha_1 P_{it} + \varepsilon_{it}$ is not taken into account; where *P* is the stock price and *E* is earnings.

Economy period, i.e., 1995-2000, differs from that in other time periods. They find that the financial variables' ability to explain stock prices is significantly lower in the New Economy period. They interpret their evidence as consistent with greater stock return volatility without a change in the properties of accounting information. They also find that coefficients that map the financial variables into stock prices display large variability. Kothari and Shanken (2003) argue that interpreting value relevance regression coefficients as the market's valuation of assets and liabilities might be inappropriate in presence of high variability of the coefficients. They run cross-sectional value-relevance regressions and they also find that slope coefficients are highly volatile. They identify three reasons that might explain this pattern: (i) changing growth expectations and discount rates; (ii) time-varying bias due to correlated omitted variables; (iii) changes in the reliability of accounting numbers through time. Since investment opportunities are commonly argued to be an omitted variable in levels regression (e.g. Nelson, 1996; Eccher et. al., 1996) they include future earnings growth and future stock returns in the regressions among the explanatory variables. These two variables, meant to proxy investment opportunities, are found to be significantly related to stock returns, but their inclusion does not change qualitatively the results of the regressions. It is also shown that even aggregate growth and discount rate effects can influence the levels regression slope coefficients through a correlated omitted variables effect. In this case, the omitted variable is the present value of future cash flows, which cannot be inserted in the regression. Thus, to verify this potential problem, a regression relating the slope coefficients to measures of aggregate growth and discount rate is estimated. The results support the idea that part of the variation in coefficients is explained by change in aggregate growth and in discount rates. However, it is concluded that the observed variation is too high to be completely explained in this manner.

Alternative metrics of market reaction to accounting information

When prices (the level of prices or the change in price, i.e. returns) are related to earnings, a significant relation with the unexpected part of earnings has to be found in order to ascertain the usefulness of earnings. Therefore, this approach implicitly assumes a model that relates earnings surprise to the direction of price changes. If price volatility or trading volume are related to earnings releases, this assumption is no longer needed. Fewer works examine the reaction of price volatility or trading volume to earnings announcements to test the usefulness of accounting information. Examples of earlier research on the reaction of volatility and volume are Beaver (1968), Patell (1976) and Atiase (1985). Among the most recent works, Kross and Kim (1999) examine abnormal trading volume and absolute stock returns at earnings announcements and find that the information content of earnings is increasing. Francis et al. (1999) show that the absolute value of abnormal daily stock returns at earnings announcement increased during the period 1986-1995. Lo and Lys (2000) examine abnormal return volatility at earnings announcements and find no change over time in their sample as a whole. An interesting contribution in this field is provided by Landsman and Mayden (2002), who, by looking at both volume and volatility, find evidence that the information content of earnings is not decreasing. They use two metrics from Beaver (1968): abnormal trading volumes[18] and abnormal return volatility[19] and they document that market reaction to earnings announcement is increasing. They also focus on those factors that prior literature would suggest are most likely to affect the information content of earnings including clustering, intangible intensity, firm size, earnings predictability, non-recurring items, losses, earnings persistence, litigation risk, and sign of unexpected earnings. But taking into account changes in the composition of firms over

[18] Abnormal trading volume is defined as $AVOL_{it} = (V_{it} - \overline{V}_i) / \sigma_i$; where V is the trading volume in the announcement period, $\overline{V}$ and σ are the mean and standard deviation in trading volume in a previous estimation period.

[19] Abnormal return volatility is obtained as $AVAR_{it} = u_{it}^2 / \sigma_i^2$; where u is the abnormal return from the market model in the announcement period, σ_i^2 is the variance of the market model adjusted returns in a previous estimation period used also to compute abnormal returns.

time does not rule out the main result that the information content of earnings is increasing over time.

A parallel stream of literature investigates the relative advantages of different metrics of decision usefulness. A group of works compares the power of tests of decision usefulness based on stock prices (examples are Brown and Warner (1985) and Rohrbach and Chandra (1989)) and on trading volume (examples are Cready and Ramanan (1991 and 1995)). Cready and Hurtt (2002) extend this analysis and conduct a comparison between metrics based on stock prices and metrics based on trading volume.

Table 1. Major determinants of the usefulness of earnings

This table presents the main factors affecting the earnings/prices relation identified by the empirical literature. It also cites examples of studies that examine the specific factors, the economic justifications offered and possible methodological problems underlined.

Factors affecting the earnings/prices relation	*Economic justification and methodological issues*	*Examples of empirical studies*
Investment in intangibles	Only partly capitalized, economy increasing intangible based	Amir and Lev (1996), Lev and Zarowin (1999)
Accounting conservatism	Asymmetry between costs and revenues, increasing tendency to conservatism	Hayn (1995), Basu (1997), Givoly and Hayn (2000)
Persistence of earnings	Effect on earnings expectations, methodological problems with transitory earnings	Kormendi and Lipe (1997), Barth et al. (1999)
Timeliness of earnings	Effect on earnings expectations, methodoligical problems if prices predict earnings	Collins et al. (1996), Ryan and Zarowin (2003)
Business change	Changes in the economy not reflected by accounting procedures	Lev and Zarowin (1999)
Quality of accounting information	Effect on the prediction of future cash flows and stock returns	Lev (1989), Lev and Thiagarajan (1993)
Interest rates	Effect on the discounted present value of revisions in expectations	Collins and Kothari (1989)
Risk	Demand for the stock after the arrival of the news	Easton and Zmijewski (1989)
Growth opportunities	Related to the persistence of earnings	Collins and Kothari (1989)
Information not incorporated in earnings	Several events affecting future earnings but not reflected in current earnings	Beaver (1998)
Information not incorporated in prices	Changes in accounting methods not affecting future cash flows	Beaver (1998)
Capital structure	Different benefits for bonds and equity, signal of performance	Dhaliwal et al. (1991), Dimitrov and Jain (2006)

CHAPTER 2 – A SURVEY OF EMPIRICAL STUDIES ON THE DETERMINANTS OF ORDER AGGRESSIVENESS

1. The determinants of order aggressiveness: theory and empirical evidence

Order aggressiveness is generally defined as the preference for a more immediate execution of the transaction. Aggressiveness, thus, involves three dimensions of the order: the type, the price and the size. Even though there exists a wide literature concentrating on the first dimension and examining the choice between limit and market orders, empirical research on the three joint dimensions is very limited. To my knowledge, five articles on the determinants of order aggressiveness have been published. I review here these contributions and three insightful working papers on the issue. Biais et al. (1995)'s article represents a seminal empirical work on the determinants of order aggressiveness and it introduces an aggressiveness classification scheme for orders later used by most of the other works in this field. Griffiths et al. (2000) propose to use an ordered probit to relate aggressiveness to its determinants. Bisière and Kamionka (2000) estimate a joint model for the level of aggressiveness and the duration of orders. Ellul et al. (2003) and Lo and Sapp (2005) consider in a single model but separately the choice of the type, the price and the size of orders. Ranaldo (2004) and Beber and Caglio (2005) improve the ordered probit technique to studying order aggressiveness. Degreyse et al. (2005) study the resiliency of the market after the submission of aggressive orders. Six main determinants of order aggressiveness have been identified by theoretical literature: the depth, the spread, the volatility, the types of orders previously submitted, market momentum and the presence of informed traders. In section 2 I describe the theoretical justifications for the determinants of aggressiveness; in section 3 I critically review the empirical studies on the determinants of aggressiveness focusing attention on the different methods used. Table 1 and 2 summarize the theoretical justifications for the determinants of order aggressiveness and the main features of the empirical works, respectively.

2. The determinants of order aggressiveness

Depth

Previous empirical works hypothesize a positive (negative) relation between depth on the same (opposite) side of the market and order aggressiveness. The motivation for this relation is derived from Parlour (1998)'s model of a limit order book. She shows that a thicker quoted depth on the same side induces the submission of more market orders, whereas a thicker quoted depth on the opposite side induces the submission of more limit orders. To understand this result a direct competition effect and a potential strategic effect on order submission strategies must be distinguished. On the one hand, the competition effect implies that, when there is a thick book on the buy-side, since limit orders have a lower execution probability, buyers are incentivized to switch to market orders; on the other hand, the strategic effect implies that, when there is a thick book on the buy-side, sellers rationally anticipate the crowding out effect of buy limit orders and thus prefer to submit more limit orders. Biais at al. (1995) argue that the impact of depth on order submission strategies is particularly marked when the spread is large, in which case market orders are very costly and new orders within the spread are an attractive alternative.

Spread

A negative relation between the spread and order aggressiveness is generally hypothesized by studies examining the order flow. The traditional argument is that traders offer liquidity when it is scarce and consume liquidity when it is abundant: when spreads are low it is optimal to submit aggressive orders and when spreads are high it is too costly to submit aggressive orders and it optimal to submit orders that do not demand immediate execution. Handa et al. (2003)' model of a limit of a limit order book offers an analytical description for a negative correlation between the spread and order aggressiveness. They show that when the distribution of the different private valuations of the asset traded becomes more uneven, the spread reduces because the cost of non-

execution borne by liquidity suppliers is lower; at the same time, the competition among traders with the same valuation increases and, overall, a preference for market orders over limit orders emerges.

Volatility

The effect of volatility on order aggressiveness is a controversial issue in the theoretical literature. Hasbrouck and Saar (2002), within an analysis of volatility and limit order trading, remark that four main effects of volatility on order submission strategies have been identified. Firstly, in the model of Lo et al. (2002), the stock price follows a diffusion process and a limit order is executed when the limit price barrier is hit; they show that the execution time of the order is decreasing in price volatility; therefore, limit orders become preferable when volatility is high. Secondly, in Foucault (1999)'s model, as volatility increases, the probability that a limit order is picked off by informed traders is higher, and, requiring higher compensation for this, limit order traders behave less aggressively and quote wider spreads. In contrast to the two effects described, Cohen et al. (1981) suggest that order aggressiveness is increasing in volatility; they notice that risk averse traders have a preference for a certain outcome and, as volatility increases, limit orders are less attractive because uncertainty regarding their outcome increases. Finally, as also proposed by Foucault (1999), offsetting influences can emerge in an equilibrium setting; in particular, a shift in favor to a category of orders can be subsequently offset if traders consider the negative effect of the shift on the probability of execution of those orders.

Types of orders previously submitted

It is frequently argued that orders of a certain type tend to be followed by orders of a similar type. Biais, Hilion and Spatt (1995) propose three reasons for the succession of similar types of orders.

First, this behavior can be due to strategic order splitting; alternatively, different traders could be imitating each other; finally, there can be similar but successive reaction to the same events.

Lo and Sapp (2005) also conjecture that the number of the different types of orders submitted affect the aggressiveness of subsequent orders. In particular: (i) market orders – On the one hand, consistently with the model of Goettler et al. (2004), more aggressive orders can be submitted after information-motivated market orders to pick off incorrectly priced limit orders. On the other hand, if market orders are liquidity motivated, they cause an erosion in depth and therefore the following orders are likely to be more passive because of the increase in the cost of aggressive orders; (ii) limit orders improving the best quotes – Limit orders improving the best quotes tend to reduce the spread and thus to increase aggressiveness; (iii) cancellation of limit orders at the best quotes – If the cancellation of limit orders at the best quotes signals an inversion in the price trend, traders are expected to submit more passive orders on the same side. The cancellation of orders at the best quotes also makes market orders on the opposite side more costly and should then discourage the submission of aggressive orders on the opposite side. Finally, as limit orders at the best quotes are cancelled the competition on the same side decreases and the submission of passive orders is encouraged.

Momentum

Beber and Caglio (2006), among others, claim that market momentum should be positively related to aggressiveness on the buy side and negatively related to aggressiveness on the sell side. In fact, traders perceive that a positive price trend reduces the probability of execution of limit buy orders, but increases the probability of execution of limit sell orders. The opposite is true for negative price trends.

Information-based trading[20]

Kaniel and Liu (2006) consider a model of a quote driven market, where a group of traders is endowed with short lived information. They find that in equilibrium informed traders submit more limit orders than market orders. The larger the horizon of the information the higher the probability that an informed trader submits limit orders because execution risk decreases. On the other hand, as the level of mispricing increases the cost of not executing the trade increases and therefore the probability that informed traders use limit orders decreases since immediate execution is now optimal. Support of the predictions of the model is found by using data from the NYSE. Specifically, both a measure of perceived informativeness by the specialist and a measure of informativeness are higher for limit orders than for market orders.

Bloomfield, O'Hara and Saar (2005) design an experiment to study order submission strategies in limit order books. In the experimental markets there are informed traders, who know the value of the traded asset in advance, and liquidity traders, who have trading targets in terms of shares to buy or sell. The results show that informed traders submit more limit orders than market orders and, in addition, they submit more limit orders than liquidity traders. The intuition behind this behavior is that informed traders, knowing the true value of the asset, can place limit orders around it and supply liquidity to the market, just like dealers, making a small profit by means of the bid-ask spread. Therefore, informed traders are the best liquidity providers.

Some empirical works have tested the relation between information based-trading and order aggressiveness. Trading volume, firm size and the speed of order submission have been used as indicators of the presence of informed traders : (i) a negative relation between trading volume and private information is predicted by the model of Diamond and Verrecchia (1991) and it is consistent with the empirical findings of Brennan and Subrahmanyan (1995) and Easley et al. (1996) ; (ii) Griffiths et al. (2000) argue that the smaller is the firm size the higher are information

[20] The first theoretical studies on order submission strategies do not incorporate informed traders; in subsequent works, for example Glosten (1994) and Seppi (1997), informed traders' strategies are exogenous; only in the most recent

asymmetries ; (iii) in the model of Easley and O'Hara (1992) trading and nontrading times have an information content : Ranaldo (2004), resting on this argument, maintains that a fast process of order submission can indicate a high arrival rate of informed orders.

3. Empirical studies on the determinants of order aggressiveness

Biais et al. (1995)

Dataset and aggressiveness classification - The object of study is the Paris Bourse[21] and the dataset consists of the 40 stocks in the CAC40 index for 19 trading days in October and November 1991. Orders are classified into 15 categories of aggressiveness. On the buy side there are six categories, from the most to the least aggressive: (1) orders to buy a larger quantity than that available at the best ask, where the investor specifies a limit price above the ask; (2) market orders to buy a quantity larger than that offered at the best ask, which is not allowed to walk up the book above the best ask; (3) orders to buy a quantity lower than that offered at the best ask, which results in full and immediate execution; (4) limit orders to buy within the best bid and ask quotes; (5) limit orders to buy that match the best bid; (6) limit orders to buy below the best bid; (7) cancellation of previously submitted orders to buy. Seven categories of orders on the sell side are defined analogously. The final category is "applications", which are prearranged trades put through the market at or within the best quotes.

Results: succession of similar order types - The frequencies of each of the 15 categories of orders conditional upon the type of the previous order are compared in a contingency table. The probability that a given type of order or trade occurs is larger after this event has just occurred than it would be unconditionally.

models, the strategies of informed traders are endogenously determined.

[21] In the time sample considered the Paris Bourse had already become organized as a pure computerized limit order book. In this context investors place orders through brokers and there are no market makers or floor traders with special obligations.

Results: effect of the state of the book - The observations are classified into four categories according to whether the depth at the quotes is larger or smaller than the time-series median for the given stock and whether the depth at the quotes is larger or smaller than the time series median for the given stock. The probabilities of occurrence of the different types of orders and trades, conditional on the previous state of the book are then compared. A χ^2 test allows to reject the hypothesis that the previous state of the book does not affect the probability of occurrence of orders or trades. The probability of the submission of the most aggressive orders decreases with the spread whereas the probability of the submission of the least aggressive orders increases with the spread. The results on the effect of the depth on the probability of submission of the different types of orders are not conclusive; in fact, there is an unexplained difference depending on the level of the spread. Yet, it is remarkable to notice that new orders within the bid-ask spread are more frequent when the depth is large, whereas new orders at the quotes are more frequent when the depth at the quotes is low. This could be interpreted as evidence of a trade-off between undercutting the best quote to obtain time priority and queuing up at the current quote.

Comments - This paper has become seminal in the literature on the determinants of order aggressiveness. The classification of aggressiveness proposed here has been used by most of the other works on this issue. It is the first study to document the diagonal effect, i.e. the succession of similar order types. The results on the effect of the state of the order book on aggressiveness are not robust. In fact, the conditional probabilities are compared only at a descriptive level and the only inference performed is a test for the independence of the probabilities. Moreover, only the aggregate depth at the quotes is examined and the possibility that the depth on the two sides of the book has different effects on aggressiveness is not considered.

Griffiths et al. (2000)

Dataset and aggressiveness classification – The study employs data from the Toronto Stock Exchange[22] and it considers all orders for stocks priced more than $5 during June 1997. Slightly modifying the design of Biais et al. (1995), orders are classified into 12 categories of aggressiveness. On the buy side there are 6 categories, from the most to the least aggressive : (1) orders to buy at a price greater than the best ask a size exceeding the depth at the best ask ; (2) orders to buy at a price equal to the best ask a size greater than the depth at the best ask ; (3) orders to buy at a price equal to the best ask a size less than or equal to the depth at the best ask ; (4) orders to buy at a price between the best bid and the best ask ; (5) orders to buy at a price equal to the best bid ; (6) orders to buy at a price less than the best bid. On the sell side, orders are classified symmetrically.

Results : price impact of orders – Following Chan and Lakonishok (1997), the price impact of an order is measured as the percentage increase from the pre-trade midquote to the average realized price. In order to examine the determinants of the cost of submitting an order characterized by different levels of aggressiveness, the price impact of an order is regressed on dummy variables for the aggressiveness of the order, the order size, volatility and market capitalization[23]. After controlling for the effect of order size, volatility and firm size, price impact is found to have a highly significant relation with aggressiveness. Consistently with the intuition that higher

[22] The Toronto Stock Exchange has a hybrid structure: it is based on a computerized limit order book where also market makers operate with obligations regarding the provision of liquidity.

[23]The following regression is run to estimate the impact of aggressiveness on the cost of execution: $O_{i,j} = \sum_{k=1}^{6} (C_k T_{(i,j,k)} + C_{(k+6)} T_{(i,j,k)} BD_{i,j} + C_{(k+12)} T_{(i,j,k)} OS_{i,j} + C_{(k+18)} T_{(i,j,k)} PV_{i,j} + C_{(k+24)} T_{(i,j,k)} FS_{i,j}) + e_{i,j}$; where $O_{i,j} = \ln(B_{i,j} / E_{i,j})$, $B_{i,j}$ is the volume-weighted average of the fill price for stock *i* and order *s* ; $E_{i,j}$ is the mean of the best bid-ask prices immediately prior to the order entering the book ; $T_{i,j,k}$ is a dummy for the type of order (it ranges from *k*=1 to 6) ; $BD_{i,j}$ is a dummy for buy orders ; $OS_{i,j}$ is the order size divided by the average daily volume of shares in the period March-May 1997 ; $PV_{i,j}$ is the standard deviation of the daily return of the stock in the period March-May 1997 ; $FS_{i,j}$ is the market capitalization of the firm as at the end of the last trading day of May 1997.

aggressiveness is associated to higher information content, the three most aggressive orders have positive signs, while the three most passive orders have negative signs.

Results : Opportunity costs of passive orders – To compare execution costs of orders with immediate execution and that of more passive orders a measure of opportunity costs is estimated for the unfilled part of the orders. Opportunity costs of unexecuted limit orders are computed as the product of the percentage of the order unfilled and the sum of the change in the midquote from immediately before entering the limit order until the time it is cancelled plus the execution cost of a category 1 order. This approach assumes that the trader is pre-committed to execute the transaction. Finally, to compare overall costs among different types of limit orders, the implementation shortfall is computed. The implementation shortfall is calculated as the opportunity cost of the portion of the order unfilled plus the portion of the order filled multiplied by the average price impact of the corresponding category of aggressiveness. The results show that there is a considerable opportunity cost to submitting passive orders. The opportunity costs of the unfilled portion generally offsets the negative price impact of the filled portion so that the implementation shortfall is positive. Category 4 orders have implementation shortfalls not much lower than execution costs for categories 1 and 3 orders. Categories 5 and 6 orders display the lowest implementation shortfalls.

Results : Ordered probit – An ordered probit is estimated to examine the determinants of order aggressiveness. The dependent variable is the level of aggressiveness (the analysis is performed by aggregating data on both sides, so there are six categories of aggressiveness). The explanatory variables are : (a) a dummy variable with value one if the previous order is, in whole part, immediately executable, and it has the same direction as the current order ; (b) the bid-ask spread as a proportion of the bid-ask spread midquote immediately before the order ; (c) the depth on the same side of the order, i.e. for buy (sell) orders, the depth at the bid (ask) immediately before the order ; (d) the depth on the opposite side of the order, i.e. for buy (sell) orders, the depth at the ask (bid) immediately before the order. All the estimated coefficients are significantly different from

zero according to the odds ratio test suggested by Griffiths and White (1993). The relation between aggressiveness and the explanatory variables is analyzed by looking at the sign of the estimated coefficients. The dummy variable for previous aggressive orders is positively related with aggressiveness, thus confirming the succession of similar order types. The spread is negatively related with aggressiveness and it is argued that higher spreads provide traders with the possibility to place passive orders that take priority over other limit orders. A positive relation between the depth on the same side of the book and aggressiveness and a negative relation between the depth on the opposite side of the book and aggressiveness are found. It is argued that order priority rules encourage the submission of more aggressive orders as depth on the same side of the book increases, whereas the depth on the opposite side reduces the need to place aggressive orders.

Results : information content of aggressive orders – To examine the information content of orders, over the three-month period following order execution, excess returns over the TSE300 Index on stocks of executed orders are computed. A three-month period should allow sufficient time for private information to become public through the release of financial statements. The results show that the most aggressive orders on the buy side are associated to the highest market adjusted returns and the most aggressive orders on the sell side are associated to negative market adjusted returns. This could reflect the presence of more informed traders on the buy than on the sell side.

Comments – The main contribution of this paper is the introduction of the ordered probit as a method to study the determinants of order aggressiveness. However, only the coefficients are examined and, being the model non-linear, it is not possible to infer from them the direction of the relation between aggressiveness and the explanatory variables. Greene (1997) shows that the analysis of the coefficients allows only to describe the relation between the probability of occurrence of the extreme categories and the explanatory variables.

Bisière and Kamionka (2000)

Dataset and aggressiveness classification – The paper analyzes one stock listed in the Paris Bourse, Alcatel, in a 40 day period from October to December 1996. Orders are classified into six categories on both the buy and the sell side, according to a scheme that closely resembles the one proposed by Biais et al. (1995). From the most to the least aggressive : (1) orders at the best prices specifying a quantity greater than that available at the best price on the opposite side of the market ; (2) market orders that can only hit the best price ; (3) limit orders at the best price on the opposite side of the market specifying a quantity equal to that available ; (4) limit orders within the best quotes ; (5) limit orders at the best quotes ; (6) limit orders at prices worse than the best quotes.

Method : a model for order flow and duration – The elapsed time between two successive submitted orders (defined as duration) and the type of the next order are modeled jointly. A likelihood function of the sequence of realizations of types and durations is derived. It is shown that the likelihood function can be written as a function of the hazard functions of the durations of the different types of orders conditional on the previous realizations of the process. It is assumed that the conditional hazard functions depend on a vector of explanatory variables according to a given functional form[24]. The explanatory variables are : an indicator of the last type of order, the depth at the best ask, the depth at the best bid, the spread, the date of the last executed order and the square of the date. Thus, by maximizing the likelihood function it is possible to estimate how the explanatory variables affect the conditional hazard functions. This allows to examine the relation between aggressiveness and the explanatory variables.

Results : transition probabilities – An estimate of the transition probabilities is derived. The succession of similar order types is not generally observed. Only the most aggressive orders tend to be followed but similar types of orders.

Results : state of the book - The depth on the same side is found to be positively related with aggressiveness, whereas the depth on the opposite side is found to be negatively related with aggressiveness. The results also show that the spread is negatively related with aggressiveness.

Results : waiting times – The waiting time after an order is found to be greatest for type (5) orders ; in general, clearcut results on the effect of aggressiveness on waiting times are not found.

Comments – The paper introduces a method similar to the autoregressive conditional duration models to study the aggressiveness of orders. The results on the effect of the state of the book on aggressiveness are in line with the findings in the related literature ; however, the results on the succession of similar order types and waiting times after orders are inconclusive. A drawback of the analysis is the very limited sample, which concentrates on only one stock.

Ellul et al. (2003)

Dataset and aggressiveness classification – The paper studies 148 stocks listed in the NYSE during the week of April, 30 to May 4, 2001. Stocks are grouped into a low, a medium and a high volume category[25]. To describe order submission strategies, market events are classified in two ways. Firstly, seven events are identified: (1) cancellation of an existing buy order; (2) cancellation of an existing sell order; (3) arrival of a limit buy order; (4) arrival of a limit sell order; (5) arrival of a market buy order; (6) arrival of a market sell order; (7) no activity in a stock-specific time interval since the last event. Secondly, 13 events are identified: (1) cancellation of a buy order; (2) cancellation of an existing sell order; (3) behind the quote limit buy; (4) at the quote limit buy; (5) inside the quote limit buy; (6) marketable limit buy; (7) behind the quote limit sell; (8) at the quote

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[24] The functional form of the hazard function, *h*, is: $h_{jk}(u \mid z; \vartheta_k) = \exp(z'_{jk}\alpha_k)\dfrac{\gamma_k u^{\gamma_k - 1}}{(1+\beta_k u^{\gamma_k})}$; where *u* is the duration, *z* is the vector of explanatory variables, $\vartheta, \alpha, \beta, \gamma$ are parameters to be estimated, *k* refers to the type of order, *j* refers to the type of the previous order.

[25] The existence at the NYSE of specialists that trade both on the account of the customers and on their own account introduces an important difference with respect to the studies considering other stock exchanges and it complicates the analysis of the determinants or order submission strategies.

limit sell; (9) inside the quote limit sell; (10) marketable limit sell; (11) market buy; (12) market sell; (13) no activity in a stock-specific time interval since the last event.

Method: multinomial logit – A multinomial logit model is estimated, where the dependent variable is the event (in the two structures described) and the independent variables are: (i) percentage spread, measured as the NYSE bid-ask spread divided by the average of the bid and ask prices at the time the order is submitted; (ii) relative NYSE bid size: the size associated with the NYSE's bid price at the time of the event divided by the number of shares outstanding; (iii) relative NYSE ask size: the size associated with the NYSE's ask price at the time of the event divided by the number of shares outstanding; (iv) relative volume; (v) own return: percentage change in the stock's midpoint in the five-minute interval before the event; (vi) own return squared; (vii) market return: percentage change in the quoted spread's midpoint for the exchange traded fund mimicking the S&P500 in the five-minute interval before the event; (viii) time of the day; (ix) time from noon squared; (x) last event market buy: dummy variable that takes value one if the previous event was a buy market order and zero otherwise; (xi) last event market sell: dummy variable that takes value one if the previous event was a sell market order and zero otherwise; (xii) last event limit buy: dummy variable that takes value one if the previous event was a buy limit order and zero otherwise; (xiii) last event limit sell: dummy variable that takes value one if the previous event was a sell limit order and zero otherwise; (xiv) last event cancel buy: dummy variable that takes value one if the previous event was a cancellation of a buy order and zero otherwise; (xv) last event cancel sell: dummy variable that takes value one if the previous event was a cancellation of a sell order and zero otherwise; (xvi) private information is a measure of traders' private information and it is calculated as : [(closing NYSE quoted spread midpoint)-(order-time NYSE quoted spread midpoint)]/(order-time NYSE quoted spread midpoint); (xvii) NYSE equals national best bid/offer: a binary variable equal to one if the NYSE quoted bud and offer prices equal the NBB and NBO prices and zero otherwise. Two models are estimated corresponding to the two event structures. The model is

estimated separately for each stock. The effect of the explanatory variable on order submission strategies is examined by looking at impulse response sensitivities, defined as the change in the probability of a dependent variable caused by a one standard deviation in an explanatory variable. A new procedure to test the significance of impulse response sensitivities is developed.

Results: estimates from the multinomial logit – (a) As the spread increases the submission of market orders decreases and the submission of limit orders increases. (b) As depth on the same side increases the submission of most limit orders decreases and the submission of market orders increases. (c) It is found that elevated trading volume is associated to more trading activity, i.e. less frequent no-activity events. (d) Own return can be seen as a measure of momentum. The results show that own return in the previous five-minute interval is positively correlated with the frequency of buy orders and negatively correlated with the likelihood of sell orders. (e) Squared own-return can be interpreted as a measure of volatility. It is found that it increases the probability of all market activities. In particular the increase in non-marketable limit orders is larger than the increase in marketable limit orders. (f) The return on the market in the previous trading interval increases the likelihood of buy orders and reduces the likelihood of sell orders. (g) Time variables are significantly related to the probability of submission of the different orders. (h) The effect of last event variables on the probabilities of the events document that there is a tendency to submit similar order types. (i) Private information has a positive impact on the submission of buy orders and a negative impact on the submission of sell orders. (j) When the NYSE's quoted prices are at the NBBO prices, the likelihood of no activity increases.

Comments – The paper analyzes market activity in a wider framework than previous works on order aggressiveness. The definition of aggressiveness proposed here does not involve quantities and therefore the results are not comparable to previous findings. This is the first paper in the literature to test the significance of marginal effects of the explanatory variables on the predicted

probabilities. It also differentiates from past works since it considers a logit instead of a probit model. The time span examined is very limited.

Ranaldo (2004)

Dataset and aggressiveness classification – The dataset consists of 15 stocks listed in the Zurich Stock Exchange[26] in the period from March to April 1997. The classification of orders follows a modification of the scheme proposed by Biais et al. (1995) and five categories on the buy and on the sell side of the book are identified. The categories, from the most to the least aggressive are : (1) market orders to buy (sell) a greater quantity than available at the best ask (bid) ; (2) market orders to buy (sell) a lower quantity than available at the best ask (bid) ; (3) limit buy (sell) orders with a price between the best quotes ; (4) limit buy (sell) orders with a price less than or equal than the best ask (bid) ; (5) cancellations of buy (sell) orders.

Method : ordered probit – An ordered probit is estimated to examine the determinants of order aggressiveness. Separate models are estimated for the buy and for the sell side of the book. The dependent variable is the level of aggressiveness and the explanatory variables are : depth on the same side of the book, depth on the opposite side of the book, spread, volatility, speed of order submission. To avoid multivariate biases different specifications are estimated where only subgroups of the explanatory variables are included in the regression. To assess the relation between aggressiveness and the explanatory variables both the coefficient of the ordered probit and marginal effects computed in correspondence of the means of the regressors are analyzed.

Results : depth – A negative relation between depth on the opposite side of the book and aggressiveness is found. The results regarding the relation between depth on the same side of the book and aggressiveness, however, are conflicting. In fact, a thicker book on the buy side is associated to higher aggressiveness of buy orders, whereas a thicker book on the sell side is associated to lower aggressiveness of sell orders. Moreover, the size of the coefficient relating

aggressiveness and depth signals that buyers are more concerned about the opposite side of the book, while sellers are more concerned about their own side. Differences in the number of informed traders, institutional traders and liquidity traders between the two sides of the book are suggested to be possible explanations for the observed different behavior of buyers and sellers.

Results : spread – The results show that there is a negative relation between the spread and aggressiveness.

Results : volatility – Volatility is measured by the standard deviation of the most recent 20 continuously compounded midquote returns. A univariate model where volatility is the only regressor is first estimated to avoid problems of multicollinearity. Volatility is then also included among the regressors of the previously described multivariate model. The estimates from the univariate model indicate that the relation between volatility and aggressiveness is negative, whereas the estimates from the multivariate model indicate a positive relation. The multivariate model is then estimated after replacing volatility by an instrumental variable orthogonal to the spread and correlated to volatility (the residuals from the least square regression of volatility on the spread). This specification documents again a positive relation between volatility and aggressiveness. This suggests that the trader's decision conditional on a wider information set including the state of the order book is different from the univariate case. It is argued that these findings could be consistent with Handa et al. (2003) model, which predicts that the volatility of prices and the aggressiveness of order submission are determined by differences in the proportion of high and low valuation investors. In fact, the results show that order imbalance, used as a proxy for the proportion between high and low valuation investors, is significantly related to order aggressiveness.

Results : waiting time – The speed of order submission is measured by the average waiting time between the last three subsequent orders. It is found to be negatively related to aggressiveness. It is

[26] The Zurich Stock Exchange is a pure electronic limit order book, without market makers.

claimed that the speed of order submission can be related to the arrival of informed traders and information endowments can thus explain the results.

Results : limit vs market order traders – The results show that most of the changes affecting the order book determine opposite marginal reactions to limit and market order traders. This could reflect the different strategies of urgent and patient traders often described in the theoretical literature.

Comments – This paper refines the method first introduced by Griffiths et al. (2000) to analyze the determinants of order aggressiveness by considering the marginal effects of the regressors in the ordered probit model. Yet, the results are not totally convincing because the marginal effects are computed only in correspondence of the means of the explanatory variables and the non-linear nature of the relation between aggressiveness and the regressors does not allow to rule out the possibility of non-monotonic patterns contradicting the results described. A further concern arises from the measure of the spread, which is not standardized on the midquote; thus, the higher the price, the higher the importance of the stock in explaining the variations in order aggressiveness.

<u>Lo and Sapp (2005)</u>

Dataset and aggressiveness classification – The paper uses data for the Deutsche Mark – US Dollar exchange rate from the Reuters D200-2 system from the 5th to the 10th of October 1997. Aggressiveness is defined only in terms of prices and six categories are identified: (1) market orders; (2) marketable limit orders (limit orders at prices better than the best price standing on the opposite side of the market); (3) best limit orders placed at prices better than the existing price; (4) best limit orders placed at the existing best price; (5) off-best orders placed within one pip of the best price; (6) off-best orders placed more than one pip away from the best price. Cancelled orders are also classified into three categories: (1) limit orders cancelled more than two pips from the best

quote; (2) limit orders cancelled between zero and two pips from the best quotes; (3) limit orders cancelled at the best order.

Method: simultaneous ordered probit and quantity regressions – Two simultaneous equations are estimated: (i) an ordered probit relating aggressiveness to market explanatory variables and to the quantity; (ii) a censored regression (used because about half of the orders are in unit quantity) relating quantity to market explanatory variables and to aggressiveness[27]. It is claimed that this allows to examine the choice of the quantity precisely, while previous works concentrated only on specific combinations of quantity and price. Separate models for the buy and for the sell side are estimated. A further orderd probit is estimated relating the different categories of cancelled orders to market explanatory variables and to the quantity. Both for submitted orders and for cancelled orders two specifications, characterized by different market explanatory variables, are estimated: (a) depth model - The explanatory variables are: volatility, depth at the best quotes, depth at the off-best quotes, differences between the best and worst prices, proportion of positive or negative price changes, number of large orders at the best quotes / number of all orders at the best quotes, number of large best bid orders / number of all best bid orders, time of the day; (b) change in state model – The explanatory variables are: volatility, number of market orders executed, number of best orders submitted, number of quotes between best orders submitted, number of best orders cancelled, number of quotes behind best quotes cancelled, time of the day. To remove intraday seasonality the method proposed by Gallant et al. (1992) is used. The results are analyzed in terms of coefficients and marginal effects computed in correspondence of the means of the explanatory variables.

Results: depth model – The results for the main explanatory variables are: (a) A negative relation is found between price aggressiveness and quantity. Two possible explanations for this behavior are suggested. Firstly, larger market orders can be subject to greater price risk since they may have to

walk up the order book and large limit orders can carry a larger adverse selection risk. Secondly, larger orders can convey more information to the market. (b) Volatility is measured in two dimensions: common volatility (obtained as the standard deviation of the midquote) and the volatility associated with only the ask or the bid side of the market (obtained as the residual of the regression of volatility from one side of the market on both the common volatility and the volatility from the opposite side of the market). It is found that both bid and ask orders become more aggressive and quantity increases as common volatility increases. However, order aggressiveness and quantity respond differently to volatility from the same and the opposite side of the market. In fact, as residual volatility from the opposite side increases both aggressiveness and quantity increase, whereas as residual volatility from the same side increases both aggressiveness and quantity decrease. (c) Depth at the best quote on the same side is found to reduce aggressiveness and quantity, while depth at the best quote on the opposite side increases aggressiveness and quantity. Depth at the off-best price has an analogous relation with aggressiveness and quantity. (d) An increase in the proportion of positive price changes leads to ask (bid) orders being submitted at more (less) aggressive prices. The reverse happens after negative price changes. The proportion of changes in one direction can be interpreted as an indicator of market momentum. (e) When there are more large orders in either side of the market, the subsequent order size increases. This can be interpreted as evidence confirming the diagonal effect.

Results: change-in-state model – The results for the quantity and volatility are similar to those from the depth model. These are the results for the main explanatory variables: (a) An increase in the execution of market or marketable limit orders on the same side leads aggressiveness and quantity to decrease. On the contrary, as execution of market or marketable limit orders on the opposite side increases, aggressiveness and quantity decrease. (b) Traders are more likely to submit less

[27] The latent regression model for aggressiveness is $I^* = \gamma_1 qn^* + \beta^{I^*} x^{I^*} + \varepsilon^{I^*}$, whereas the latent quantity model is $qn^* = \alpha + \gamma_2 I^* + b^{qn} x^{qn} + \varepsilon^{qn}$; where I^{*I^*} is the latent value of aggressiveness, x is a set of explanatory variables,

aggressive orders on the same side of the market as the number of limit orders placed on the same side increases. The opposite holds for an increase on the opposite side of the market. (c) The cancellation of off-best limit orders on the same side of the market induces the submission of more aggressive orders. The opposite is true for cancelled orders on the opposite side of the market. Mixed results are obtained for cancelled ordered at the best quotes.

Results: the impact of market performance - Dummy variables for market trend (a dummy for positive trend, a dummy for negative trend and a dummy for stable prices) are included in the model to keep track of the impact of market performance on the relation between aggressiveness, quantity and the explanatory variables. The impact of the explanatory variables on aggressiveness and quantity does not generally change qualitatively after controlling for market performance.

Results: cancellation of orders – The probability of the different categories of cancellations is found to be affected by the explanatory variables both in the depth model specification and in the change-in-state model specification.

Comments – The definition of aggressiveness given in the paper is different from the one proposed by the other works in this literature since it does not take into account quantity[28]. As a consequence the results are not comparable to the previous findings. It follows that, for example, depth and volatility are found to have the opposite effect on aggressiveness than the effect previously documented. The paper further differentiates from the other works since it considers a foreign exchange market. A possible limitation of the analysis is that the time span considered consists only of five days.

<u>Beber and Caglio (2005)</u>

Dataset and aggressiveness classification – The paper studies ten stocks listed in the New York Stock Exchange in the period between November 1990 and January 1991. These are the stocks that

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qn^* is the latent value of quantity.

display highest trading volume in the TORQ database during the three-month sample[29]. The analysis considers orders placed in the limit order book during the continuous auction phase of trading. Orders are classified into six categories of aggressiveness, according to a scheme similar to Biais et al. (1995) : (1) either buy (sell) market orders or buy (sell) limit orders for a price greater (less) than or equal to the best ask (bid), both submitted for a quantity of shares larger than the corresponding quoted depth; (2) buy (sell) market orders and buy (sell) limit orders for a price greater (less) than or equal to the best ask (bid) and with a smaller size than the quoted depth; (3) buy (sell) limit orders for a price that lies between the bid and the ask; (4) buy (sell) orders for a price equal to the bid (ask); (5) buy (sell) limit orders for a price less than the bid (ask) and with a distance from the bid (ask) up to four ticks; (6) buy (sell) limit orders for a price less than the bid (ask) and with a distance from the bid (ask) greater than four ticks.

Method: ordered probit – An ordered probit is estimated relating aggressiveness to its determinants. Two separate models are estimated for the buy and the sell side of the book. The dependent variable is the level of order aggressiveness and the explanatory variables are: depth on the buy side, depth on the sell side, spread, momentum, volatility, time of the day, trading activity (measured alternatively by transacted volume or time between transactions). Both the coefficients of the ordered probit and marginal effects computed in correspondence of the means of the regressors are analyzed in order to describe the relation between aggressiveness and the explanatory variables.

Results : depth – For both buyers and sellers, aggressiveness is found to be increasing in the depth on the same side of the book. Conversely, buyers and sellers react differently to changes in the depth on the opposite side of the book. Aggressiveness of buyers is decreasing in the depth on the sell side, whereas aggressiveness of sellers is increasing in the depth on the buy side. To explain

[28] The analysis considers only two dimensions of aggressiveness: the price and the type of the order. The size of the order is jointly modeled but it is not considered to determine the level of aggressiveness.

[29] As remarked for Ellul et al. (2003), the existence of specialists at the NYSE makes it difficult to examine the response of traders to changes in the trading environment.

this asymmetry, it is claimed that this can reflect the presence of more liquidity motivated traders on the sell side and that sellers can be more impatient than buyers.

Results : spread – The relation between the spread and aggressiveness is found to be negative for both buyers and sellers. When the square of the spread is also included among the regressors to control for non-linear effects, a negative relation between the spread and aggressiveness is confirmed.

Results : volatility – Volatility is measured by an exponential moving average of the squared returns of trade prices. The measure of volatility is included among all the other explanatory variables in the model. For both buy and sell orders the results show that volatility is negatively related to aggressiveness.

Results : momentum – A momentum indicator is computed as the ratio of the stock price and an exponential moving average of the price itself[30]. A stock price trend leads the indicator to diverge from one, while a stock price with no specific directional movement leads the indicator to converge to one. It is found that when there are positive price trends, buy orders become more aggressive and sell orders less aggressive. The opposite is true for negative price trends.

Results: trading activity – Two measures of trading activity are used: transacted volume and time between transactions and the results are conflicting. In fact, higher transacted volume drives more aggressive buy and sell orders, whereas a shorter time between transaction is associated to less buy and more aggressive orders. It is argued that the two indicators measure different aspects of trading activity.

Results: time of the day – Dummy coefficients are included in the model to take time-trend effects into account. The results show that orders become increasingly aggressive during the day.

[30] The momentum indicator (*MOM*) is obtained as the ratio between the stock price *P* and an exponential moving average (*EMA*) of the price itself : $EMA_t(P_t) = (1-\lambda)\sum_{i=0}^{t}\lambda^{t-i} P_i = \lambda EMA_{t-1}(P_i) + (1-\lambda)P_t$, $MOM_t = P_t / EMA_t(P_i)$, with $\lambda = 0.95$.

Results: Information and aggressiveness – The relation between aggressiveness and the presence of informed traders in the market is also examined. A measure of the probability of information-based trading is derived from the model of Easley et al. (1996). After estimating the parameters of the model, by using the frequency of trades and the imbalance of orders, the daily probability of information-based trading is computed as the ratio between the estimated arrival rate of informed trades and the estimated arrival rate of all trades. Three groups of stocks with homogeneous average transacted volume are created. Consistently with previous theoretical works, it is found that the group with the lowest transacted volume is characterized by the highest probability of information-based trading. The mean probabilities predicted by the ordered probit are compared to actual frequencies of the different types of orders across the three groups. The group with the highest probability of information-based trading displays lower aggressiveness than predicted. These findings are interpreted as evidence that informed traders prefer to use more patient trading strategies than the uniformed.

Results: Earnings announcements periods – Seven stocks in the sample released earnings figures during the sample period. The ten trading days preceding earnings announcement are analyzed by comparing theoretical probabilities predicted by the ordered probit and actual frequencies of the different types of orders. The results show that buyers are less aggressive while sellers are more aggressive than expected.

Comments – The paper represents the only contribution on the relation between order submission strategies and the release of accounting information. However, it differentiates from my analysis at least in two aspects: I concentrate on the period after the earnings announcement whereas they consider the pre-announcement period; I directly estimate the relation between unexpected earnings and order aggressiveness whereas they compare the estimated coefficients of the ordered probit in a period far from the announcement and in the pre-announcement period. As mentioned for Ranaldo

(2004), the analysis of the determinants of aggressiveness in terms of marginal effects is not conclusive.

Degreyse et al. (2005)

Dataset and aggressiveness classification – The analysis focuses on the 20 stocks traded in the Paris Bourse in the period ranging from March to August 1998 (a total of 123 trading days). Orders are classified into 6 categories on the buy and on the sell side, according to a scheme similar to Biais et al. (1995): (1) orders to buy (sell) a larger quantity than is available at the best ask (bid) at a price higher than the best ask (bid); (2) orders to buy (sell) a larger quantity than available at the best ask (bid) but that does not walk up the order book above (below) the best ask (bid); (3) orders to buy (sell) a quantity that is lower than the one offered at the best ask (bid); (4) orders to buy (sell) at a price between the best bid and the best ask; (5) orders to buy (sell) at a price lower (greater) than the best ask (bid); (6) other orders.

Results: succession of similar order types – The probability of submission of the different order types are examined in a contingency table. The analysis indicates that the probability that an order of a certain type is followed by an order of the same type is relatively high. Aggressiveness of orders following the first one is also examined: the diagonal effect persists beyond one order but the conditional probabilities converge to unconditional levels.

Results: impact of aggressive orders on the state of the book – The main objective of the paper is to investigate the market impact of aggressive orders and the resiliency of the market. To this aim the limit order book is examined in a small period of time around an order of type 1, 2, 7, 8 (the most aggressive on both sides of the market). Around the submission of an order a window of ten best limit updates before and 20 after is created. Best limit updates are defined as an update of either the best bid or ask prices, or the depth at these best prices. Within each window the variables analyzed are: best bid and ask prices, depth at these prices, spread, duration between best limit updates. (i)

Best bid and ask prices - The results show that for all stocks best prices in the book are significantly different from their value at the time of the aggressive order during the whole event window after such order. The effect of aggressive orders on prices is larger for the smallest stocks than for the largest. This effect can be interpreted as a measure of the cost associated to submitting an aggressive orders. (ii) Depth – Aggressive buy orders are found to determine a decrease in the depth at the best ask before the order and an increase afterwards; symmetrically the depth at the best bid decreases before an aggressive sell order and increases afterwards. A possible explanation for this behavior is that new liquidity is supplied after it has been consumed. Alternatively, it is suggested that the book behind the best prices can be deep and this can show up after a trade that wipes out the volume at the best quotes. (iii) Spread and duration – Spreads are found to decrease before aggressive orders and increase afterwards. After the decrease in the spread, aggressive orders are submitted quickly, which is documented by the fact that the average duration between best limit updates is much shorter around aggressive orders. After aggressive orders, the increase in the spread lasts for some orders in the future. Both duration and spread remain significantly above the pre-aggressive order levels. It is claimed that this pattern might indicate that before the submission of an aggressive order the spread is rather low compared to a normal situation.

Results: impact of aggressive orders on transaction prices – To examine the impact of aggressive orders on transaction prices a window of ten best limit updates before the order and 20 after is created. It is found that transaction prices increase before an aggressive buy order and decrease before an aggressive sell order. This evolution is partially reversed after the submission of the orders. Correlations between price changes around aggressive orders are also analyzed. The results confirm that after the first transaction part of the effect of an aggressive order in transaction prices is reversed.

Comments – The paper focuses on the effect of aggressive orders on the state of the order book and on prices. However, it also contributes to the debate on the determinants of order aggressiveness by

showing that market variables are different from their normal values when aggressive orders are submitted. The estimate of the cost of aggressive orders is more precise than the one proposed by Griffiths et al. (2000), since it considers the effect of the orders over a wider time span.

Table 1. Predicted relations between aggressiveness and its main determinants

This table shows the sign of the predicted relations between aggressiveness and its main determinants identified by theoretical and empirical studies.

Determinant of aggressiveness	*Predicted relation*	*Theoretical justification or model*
(1.a) Depth on the same side	- Positive	- Competition effect – Parlour (1998)
(1.b) Depth on the opposite side	- Negative	- Crowding out effect – Parlour (1998)
(2) Spread	- Negative	- Cost of liquidity
	- Negative	- Correlation – Handa et al. (2003)
(3) Volatility	- Negative	- Risk of being picked off by insiders – Foucault (1999)
	- Negative	- Execution time – Lo et al. (2002)
	- Positive	- Preference for a certain execution – Cohen et al. (1981)
	- Uncertain	- Equilibrium considerations – Foucault (1999)
(4) Previous order type	- Positive	- Splitting, imitation, similar reaction
(5) Momentum	- Positive on buy and negative on sell	- Effect on the probabilities of execution of limit orders
(6) Information-based trading	- Negative	- Lifetime of information – Kaniel and Liu (2006)

Table 2. Empirical studies on the determinants of order aggressiveness

This table summarizes the main features of the eight contributions on the determinants of order aggressiveness described in section 3. The results of the tests are not reported since a monotonic relation between aggressiveness and the explanatory variables is not generally found.

Article and journal of publication	*Dataset considered*	*Main determinants of aggressiveness tested*	*Method to study aggressiveness*	*Other issues related to aggressiveness*
Biais et al. (1995) [Journal of Finance]	Paris Bourse, CAC40 stocks, 19 trading days, year 1991	- Depth - Spread - Previous order type	Contingency table of conditional probabilities	
Griffiths et al. (2000) [Journal of Financial Economics]	Toronto Stock Exchange, stocks priced more than 5 $, 1 month, year 1997	- Depth same side - Depth opposite side - Spread - Previous order type	Ordered probit	- Costs of aggressive orders - Information content of orders
Bisière and Kamionka (2000) [Annales d'économie et de statistique]	Paris Bourse, 1 stock, 40 trading days, year 1996	- Depth same side - Depth opposite side - Spread - Previous order type	Joint model (ACD) of type and duration	- Waiting times after orders
Ellul et al. (2003) [Working paper]	NYSE, 148 stocks, 1 week, year 2001	- Depth same side - Depth opposite side - Spread - Volatility - Momentum - Private information	Multinomial logit	- Market events as functions of aggressiveness determinants
Ranaldo (2004) [Journal of Financial Markets]	Zurich Stock Ecxhange, 15 stocks, 2 months, year 1997	- Depth same side - Depth opposite side - Spread - Volatility - Speed of submissions	Ordered probit	
Lo and Sapp (2005) [Working paper]	Deutsche Mark – US Dollar exchange rate from the Reuters D200-2 system, 1 week, year 1997	- Depth same side - Depth opposite side - Depth off-quotes - Previous order type - Momentum - Quantity - Trading volume - Previous order type - Volatility buy/sell - Number of different types of orders previously submitted	Simultaneous ordered probit (for aggressiveness) and censored regressions (for quantity)	
Beber and Caglio (2005) [Working paper]	NYSE, 10 stocks, 3 months, year 1991	- Depth same side - Depth opposite side - Spread - Volatility - Momentum - Information based trading - Trading volume	Ordered probit	- Aggressiveness before earnings announcements
Degreyse et al. (2005) [Review of Finance]	Paris Bourse, 20 stocks, 123 trading days, year 1998	- Depth - Spread - Duration - Best prices - Previous order type	Comparison of explanatory variables in a window around the order	- Resiliency of the market after aggressive orders

CHAPTER 3 – ORDER AGGRESSIVENSS AS A METRIC OF DECISION USEFULNESS: EVIDENCE FROM THE ITALIAN STOCK EXCHANGE

1. An application of order aggressiveness as a metric of decision usefulness

In this chapter I test the usefulness of earnings announcements of firms listed in the Italian Stock Exchange limit order book by examining the reaction of order aggressiveness to unexpected earnings. Section 2 presents the motivation of the empirical analysis; section 3 describes the dataset; section 4 is devoted to the specification of the empirical model; section 5 comments the results; section 6 concludes.

2. Motivation

As introduced in chapter 2, order aggressiveness is generally defined as the preference for a faster execution. In limit order books, two main categories of orders exist: limit orders, where traders specify both a price and a quantity, and market orders, which are at best orders. Market orders are more aggressive than limit orders because they are executed immediately. A further categorization of aggressiveness can be obtained by considering how prices and quantities of orders are related to the speed of execution. As in most previous works, I use a refinement of the aggressiveness classification proposed by Biais et al. (1995). Spread, depth and volatility are the major market determinants of order aggressiveness identified by other studies. I concentrate on unexpected earnings as a determinant of aggressiveness and I develop hypotheses 1 and 2. I examine the relation between order aggressiveness and unexpected earnings and I employ spread, depth and volatility as control variables. Finally, I propose to use the effect of unexpected earnings on traders' strategies, measured by order aggressiveness, as a metric to evaluate the usefulness of the information released.

2.1 Order aggressiveness as a metric to evaluate the usefulness of earnings

The market-based metrics that have been used to test the usefulness of information from financial statements concentrate on the reaction of stock prices and trading volume. The aggressiveness classification provides a description of order submission strategies, which in turn are the determinants of stock prices and trading volume. Thus, investigating how order submission strategies, through order aggressiveness, are affected by the release of accounting information allows a more direct test of whether the news is used by market participants. Order submission strategies are also influenced by market variables other than the release of accounting information: the analysis of the reaction of stock prices and trading volume to the release of accounting information necessarily treats those variables as noise. The advantage of a more primitive metric is that at least a part of the pattern in the noise contained in less direct metrics can be modeled.

The approach I propose presents other elements of interest that make it suitable to be complementary to the traditional approaches. Firstly, order aggressiveness reflects a larger set of information regarding market behavior than stock prices and trading volume do. In fact, not only are executed orders considered, but unfilled limit orders, which represent a large portion of orders submitted, are also classified. On the contrary, stock prices and trading volume directly reflect only the information contained in executed orders. Secondly, the analysis of order aggressiveness exploits, by definition, intraday data, whereas the analysis of stock prices and trading volume has mostly been limited to daily data. Although in long window studies differences among trading times are likely to be irrelevant, in short window studies an intraday analysis helps capture intuitions hidden in the complexity of aggregate results. In particular, the reaction of different categories of market participants can be related to different trading times. A further interest point in examining order aggressiveness is the possibility to segment the results by the characteristics of orders. For example, the reaction of buyers and sellers can be distinguished and the size of orders can be related

to the reaction. This can contribute to the field of research on how individuals and institutions trade when accounting information is disclosed.

In general, order aggressiveness does not move in the same direction as stock prices and trading volume. It is easy to show examples in which the traditional metrics based on prices and volume do not imply usefulness of information, but a metric based on order aggressiveness does. Suppose that the best ask is equal to *a* and the best bid is equal to *b*. On day 1 two orders are submitted: a market sell order that hits *b* and then a limit buy order at a price *b*. The price registered at the end of day 1 is therefore *b*. On day 2 two orders are also submitted: a market buy order that hits *a* and then a market sell order that hits *b*. The price registered at the end of day 2 is again *b* and there has been no price movement. By contrast, there has been an increase in aggressiveness because market orders are considered more aggressive than limit orders since they demand immediate execution[31]. Suppose now that the best ask is equal to *a* and the best bid is equal to *b* as in the previous example. On day 1 two limit buy orders at a price less than *b* are submitted. On day 2 two limit orders are submitted: a buy order at a price *c* greater than *b* and less than *a* and then a sell order at a price less than *a* and greater than *c*. Here trading volume has not changed but trading aggressiveness has increased because on day 2 orders inside the bid-ask spread (which are likely to be executed faster than orders outside the bid-ask spread) have been submitted.

2.2 Unexpected earnings and order aggressiveness

Microstructure literature has examined how the problem of a trader who has to choose whether to submit a limit or a market order is related to the value of private information. It is generally found that the further the expectations deviate from the price, the more aggressive the type of order optimally submitted. The bottom line of the theoretical works on this issue is that a limit order allows a price improvement with respect to the outstanding quotes but is not necessarily executed;

[31] I assumed here that the closing price is computed as the last transaction price. If the closing price is computed as a weighted average of all transaction prices, an analogous example can be imagined.

conversely, a market order is executed against the outstanding quotes, but it is surely executed and thus it does not bear execution risk. In the model of Angel (1994), an informed trader compares the expected profits deriving from a certain trade through a market order and an uncertain trade at more favorable prices through a limit order; he shows that the relative advantage of submitting a market order increases with the deviation of the price from its expected value. In the models of Harris (1998) and Kaniel and Liu (2006), the choice between a limit and a market order depends on the magnitude of the expected mispricing and on how long the mispricing prevails, which is interpreted as the horizon of the private information. They both find that as the magnitude of the mispricing increases, the probability of submitting market orders increases because of the increase in the cost of non-execution. Bloomfield et al. (2005) provide experimental evidence supporting the predictions of the models described: when the value of the experimental asset is extreme and thus the value of information is greater because the quoted price is far from the fundamental, traders are more likely to submit market orders. Resting on these contributions, I formulate the following hypotheses[32]:

Hypothesis 1: The higher the absolute value of unexpected earnings, the more aggressive the orders submitted on the buy side

Hypothesis 2: The higher the absolute value of unexpected earnings, the more aggressive the orders submitted on the sell side

2.3 Control variables - The market determinants of order aggressiveness[33]

SPREAD – A negative relation between the spread and order aggressiveness is generally hypothesized by studies examining the order flow. The traditional argument is that traders offer liquidity when it is scarce and consume liquidity when it is abundant: when spreads are low it is

[32] In the empirical analysis, I discriminate the effect of the information release on buyers and on sellers. Therefore, I formulate separate hypotheses for the two sides of the market.

optimal to submit aggressive orders and when spreads are high it is too costly to submit aggressive orders and hence it is optimal to submit orders that do not demand immediate execution. Handa et al. (2003)' model of a limit order book offers an analytical description for a negative correlation between the spread and order aggressiveness. They show that when the distribution of the different private valuations of the asset traded becomes more uneven, the spread reduces because the cost of non-execution borne by liquidity suppliers is lower; at the same time, the competition among traders with the same valuation increases and, overall, a preference for market orders over limit orders emerges.

A negative relation between the spread and order aggressiveness is consistent with the empirical findings of Biais et al. (1995), Griffiths et al. (2000), Handa et al. (2003), Ranaldo (2004), Beber and Caglio (2006).

DEPTH – Previous works hypothesize a positive (negative) relation between depth on the same (opposite) side of the market and order aggressiveness. The motivation for this relation is derived from Parlour (1998)'s model of a limit order book. She shows that a thicker quoted depth on the same side induces the submission of more market orders, whereas a thicker quoted depth on the opposite side induces the submission of more limit orders. To understand this result a direct competition effect and a potential strategic effect on order submission strategies must be distinguished. On the one hand, the competition effect implies that when there is a thick book on the buy-side, since limit orders have a lower execution probability, buyers are incentivized to switch to market orders; on the other hand, the strategic effect implies that when there is a thick book on the buy-side, sellers rationally anticipate the crowding out effect of buy limit orders and thus prefer to submit more limit orders. Biais at al. (1995) argue that the impact of depth on order submission strategies is particularly marked when the spread is large, in which case market orders are very costly and new orders within the spread are an attractive alternative.

[33] In this subsection I summarize the description of the relation between aggressiveness and market variables presented in chapter 1. Chapter 1 also considers how aggressiveness is related to the types of orders previously submitted, to

This type of relation between depth and order aggressiveness is consistent with the empirical findings of Biais et al. (1995), Griffiths (2000), Ranaldo (2004), Beber and Caglio (2006).

VOLATILITY – The effect of volatility on order aggressiveness is a controversial issue in the theoretical literature. Hasbrouck and Saar (2002), within an analysis of volatility and limit order trading, remark that four main effects of volatility on order submission strategies have been identified. Firstly, in the model of Lo et al. (2002), the stock price follows a diffusion process and a limit order is executed when the limit price barrier is hit; they show that the execution time of the order decreases with price volatility, therefore limit orders become preferable when volatility is high. Secondly, in Foucault (1999)'s model, as volatility increases, the probability that a limit order is picked off by informed traders is higher, and, requiring higher compensation for this, limit order traders behave less aggressively and quote wider spreads. In contrast to the two effects described, Cohen et al. (1981) suggest that order aggressiveness increases with volatility; they notice that risk averse traders have a preference for a certain outcome and, as volatility increases, limit orders are less attractive because uncertainty regarding their outcome increases. Finally, as also proposed by Foucault (1999), offsetting influences can emerge in an equilibrium setting; in particular, a shift in favor to a category of orders can be subsequently offset if traders consider the negative effect of the shift on the probability of execution of those orders.

A negative relation between volatility and order aggressiveness is consistent with the empirical findings of Ranaldo (2004) and Beber and Caglio (2006). A positive relation between volatility and order aggressiveness is consistent with the empirical findings of Hasbrouck and Saar (2002) and Lo and Sapp (2005).

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information-based trading and to market momentum.

3. The dataset

I consider data from the continuous trading phase of the Mercato Telematico Azionario (MTA) at the Italian Stock Exchange. The sample consists of the 40 firms of the S&P/MIB index[34], which includes the stocks with the highest capitalization and trading volume. For each stock I examine the 'yearly earnings' announcement day and the two following days in the years 2003, 2004 and 2005. I use the corresponding analysts' forecasts of earnings provided by I/B/E/S. I obtain data on reported earnings, closing prices and daily trading volumes from Datastream. Overall, I analyze the market response to 99 earnings announcements[35].

3.1 The trading structure and the classification of order aggressiveness

The stocks of the S&P/MIB index are traded in the MTA, the main trading environment of the Italian Stock Exchange. In the MTA the trading day is divided into three phases: an opening call auction, from 8:00 to 9:00, a continuous trading phase, from 9:00 to 17:25 and a closing call auction, from 17:25 to 17:35. I only examine data from the continuous trading phase, which is organized as a pure electronic limit order book.

During the continuous trading phase, traders submit orders which are matched by a centralized mechanism. The two main categories of orders are: (i) limit orders – which indicate a limit price; (ii) market orders – which do not indicate a price, they are orders at the best quote. Orders can be submitted with time parameters as: (i) VSC (valid until cancellation) – valid until the end of the trading day unless cancelled; (ii) VSD (valid until a specified date) – continues to be active after the end of the trading day, until a specified date; (iii) VAC (valid only in the closing auction) – is valid

[34] I consider the stocks in the S&P/MIB index in June 2005: AEM (AEM), Autogrill (AGL), Alleanza (AL), Autostrade (AUT), Banca Fideuram (BFI), Banca Intesa (BIN), Banca Nazionale del Lavoro (BNL), Banca Popolare di Milano (BPM), Banche Popolari Unite (BPU); Banca Popolare di Verona e Novara (BPVN), Bulgari (BUL), Capitalia (CAP), ENEL (ENEL), ENI (ENI), Espresso (ES), Fiat (F), Finmeccanica (FNC), Fondiaria Sai (FSI), Fastweb (FWB), Generali (G), Italcementi (IT), Lottomatica (LOTT), Luxottica (LUX), Mediobanca (MB), Mediolanum (MED), Mondadori (MN), Banca Monte dei Paschi (MPS), Banca Antonveneta (NTV), Pirelli & Company (PC), Rizzoli (RCS), Seat Pagine Gialle (SPG), San Paolo Imi (SPI), Saipem (SPM), Snam Rete Gas (SRG), STMicroelectronics (STM), Terna (TRN), Unicredito (UC).

only after the continuous trading phase (I do not consider this kind of orders). Orders can be placed with quantity parameters as: (i) EEC (fill and kill) – when part of the order is executed, the order is cancelled; (ii) EQM (execute minimum quantity) – if the minimum quantity is not immediately available, the order is cancelled; (iii) TON (fill or kill) – if the total quantity is not immediately available, the order is cancelled; (iv) ECO (execute anyway) – a parameter for market orders which allows the order to walk up the book to have a complete execution; (v) hidden orders –a parameter for limit orders which indicates that a part of the order is hidden before a specified price is reached (I do not have data on hidden orders). Orders are matched according to price and time priority rules as follows: (a) limit buy (sell) orders are matched with one or more limit sell (buy) orders with lower (greater) or equal price. (b) market buy (sell) orders are matched with one or more limit sell (buy) orders with the lowest (highest) price in the book. When a market order is partially executed, a limit order is automatically submitted with a price equal to the last transaction price registered and with the same time priority of the original order. When a limit order is partially executed, a limit order is automatically submitted with the same price and time priority of the original order.

I use a classification of order aggressiveness derived from Biais et al. (1995) and I divide orders into ten groups. On the buy side I define the following five categories of orders, corresponding to decreasing degrees of aggressiveness. Orders of type 0 are: market orders to buy a quantity larger or equal to that available at the best ask; limit orders to buy at a price greater or equal to the best ask a quantity larger or equal to that available at the best ask. Type 0 orders are marketable limit orders (i.e. at best limit orders) and market orders with or without parameter ECO. Orders of type 1 are: market orders to buy a quantity lower than that offered at the best ask; limit orders to buy at a price higher or equal to the best ask a quantity lower than that available at the best ask. Type 1 limit and market orders are equivalent because they are both immediately totally executed. Type 2 are limit orders to buy at a price greater than the best bid and lower than the best ask. Type 3 are limit orders

[35] I had to exclude from the dataset the announcements for which data on forecasts or on the order book were not completely available. I also excluded one stock (Mediobanca) because its fiscal year does not end on December 31.

to buy at a price equal to the best bid. Type 4 are limit orders to buy at a price lower than the best bid. On the sell side orders are defined symmetrically.

Figure 1 shows examples of orders for each category of aggressiveness. Table 1 presents the relative frequencies of the different categories of orders and figure 2 compares the absolute frequencies.

3.2 Unexpected earnings and control variables

I use three measures of unexpected earnings frequently employed in the literature on decision usefulness of accounting information[36]: (1) The difference between reported earnings per share and the mean earnings per share (consensus) forecast by analysts. I take the last data on analysts' consensus published before the earnings announcement. (2) The yearly difference in reported earnings per share. (3) Standardized unexpected earnings (*SUE*), computed as: $SUE = \frac{e_q - e_{q-4}}{\sigma}$; where e is earnings per share, q refers to the quarter and σ is the standard deviation of unexpected earnings, $e_q - e_{q-4}$, over the preceding eight quarters.

I measure the spread by the difference between the best ask and the best bid as a percentage of the midquote. I measure depth on the bid and on the ask side by the number of shares outstanding at the best quotes. Following Ranaldo (2004), I measure volatility by the standard deviation of the last 20 midquote returns.

Table 2 presents descriptive statistics for the market determinants of order aggressiveness and for the three measures of unexpected earnings.

[36] Examples of papers that use analyst forecasts as the benchmark for unexpected earnings (measure 1) are Arbanell and Bernard (1992), Bartov et al. (2002) and Liang (2003). The seasonal difference in earnings (measure 2) is mostly used by the first studies (for example Ball and Brown (1968), Brown and Kennelly (1972)) on the information content of earnings. The seasonal difference in earnings standardized on the standard deviation of previous differences (measure 3) is used, for example, by Foster et al. (1984), Chan et al. (1996), Livnat and Mendenhall (2006)).

4. Empirical methods

I examine order aggressiveness by estimating an ordered probit model, an approach to the analysis of order aggressiveness first introduced by Griffiths et al. (2000). I jointly analyze the buy side and the sell side of the market. The dependent variable is the category of order aggressiveness, which takes values from zero to four. The explanatory variables are: unexpected earnings, spread, depth on the bid side, depth on the ask side, volatility, and a dummy variable for sell orders (henceforth *DS*). I estimate three specifications of the model, corresponding to the three measures of unexpected earnings described. I also estimate a simple model where unexpected earnings are not included among the explanatory variables.

<u>Model estimation</u>

I assume that an unobserved random variable, y_i^*, is related to the explanatory variables of order aggressiveness in a linear fashion: $y_i^* = x_i'\beta + \varepsilon_i$; where x_i is a (11×1) vector containing the explanatory variables (x_{i1}: |unexpected earnings|; x_{i2}: spread; x_{i3}: depth bid; x_{i4}: depth ask; x_{i5}: volatility; x_{i6}: *DS*; x_{i7}: $DS \times$ (|unexpected earnings|); x_{i8}: $DS \times$ (spread); x_{i9}: $DS \times$ (depth bid); x_{i10}: $DS \times$ (depth ask); x_{i11}: $DS \times$ (volatility)), ε_i is conditionally normally distributed with mean zero and variance σ^2. The subscript *i* refers to the observation number.

The observed level of order aggressiveness, denoted by y_i, is related to y_i^* as follows:

$$y_i = \begin{cases} 0 & \text{if} \quad y_i^* < \alpha_1 \\ 1 & \text{if} \quad \alpha_1 \le y_i^* < \alpha_2 \\ 2 & \text{if} \quad \alpha_2 \le y_i^* < \alpha_3 \\ 3 & \textit{if} \quad \alpha_3 \le y_i^* < \alpha_4 \\ 4 & \text{if} \quad y_i^* \ge \alpha_4 \end{cases}$$

where $\alpha_1, ..., \alpha_4$ are the parameters characterizing the partition on which y_i^* is defined.

It is possible to derive the probability of observing the different categories order aggressiveness conditional on x_i and the parameters to be estimated[37]. In general, for the five categories, the conditional probability can be written as:

$$\Pr(y_i = j) = \begin{cases} \Phi(\frac{-x_i'\beta + \alpha_1}{\sigma}) & , \quad j = 0 \\ \Phi(\frac{-x_i'\beta + \alpha_{j+1}}{\sigma}) - \Phi(\frac{-x_i'\beta + \alpha_j}{\sigma}) & , \quad 1 \le j \le 3 \\ 1 - \Phi(\frac{-x_i'\beta + \alpha_7}{\sigma}) & , \quad j = 4 \end{cases}$$

The model is estimated through the maximum likelihood method. The logarithm of the likelihood function is given by:

$$L = \sum_{i=1}^{n} \ln \Pr(y_i \mid x_i) =$$

$$= \sum_{i=1}^{n} \{ \; I(y_i = 0) \ln[\Pr(y_i^* < \alpha_1)] + \sum_{j=1}^{4} I(y_i = j) \ln[\Pr(\alpha_j \le y_i^* < \alpha_{j+1})] + I(y_i = 4) \ln[\Pr(y_i^* > \alpha_4)] \; \}$$

By expanding $\Pr(y_i^* < \alpha_1)$, $\Pr(\alpha_j \le y_i^* < \alpha_{j+1})$ and $\Pr(y_i^* > \alpha_4)$:

$$L = \sum_{i=1}^{n} \{ \; (I(y_i = 0) \ln[\Phi(\frac{-x_i'\beta + \alpha_1}{\sigma})] + \sum_{j=1}^{3} I(y_i = j) \ln[\Phi(\frac{\alpha_{j+1} - x_i'\beta}{\sigma}) - \Phi(\frac{\alpha_j - x_i'\beta}{\sigma})] +$$

$$+ I(y_i = 4)[1 - \Phi(\frac{-x_i'\beta + \alpha_7}{\sigma})] \; \}.$$

Using the standard assumption in ordered probit models that $\sigma = 1$, I maximize the likelihood function and I estimate the coefficients β and the cutoff parameters $\alpha_1, ..., \alpha_7$.

I compute cluster-adjusted (for stock/earnings annnouncement) standard errors by estimating the variance covariance matrix of the coefficients through the Huber-White estimator. The maximum likelihood estimators are asymptotically normally distributed, therefore I can construct a *z*-test to test the hypothesis that the coefficients are equal to zero.

[37] For example, denoting by Φ the cumulative function of the standard normal distribution, for the first category (0), the conditional probability is: $\Pr(y_i = 0) = \Pr(y_i^* < \alpha_1) = \Pr(x_i'\beta + \varepsilon_i < \alpha_1) = \Pr(\frac{\varepsilon_i}{\sigma} < \frac{-x_i'\beta + \alpha_1}{\sigma}) = \Phi(\frac{-x_i'\beta + \alpha_1}{\sigma})$. Conditonal probabilities for the other categories are derived analogously.

Interpreting change: standardized coefficients and marginal effects

Since the metric of the unobserved order aggressiveness, y^*, is unknown, the change related to the explanatory variables cannot be interpreted without standardizing the estimated standard deviation of y^*, $\hat{\sigma}^2_{y^*} = \hat{\beta}'\hat{V}ar(x)\hat{\beta} + \sigma^2$. Therefore, I present the y^*-standardized coefficients, defined as: $\beta_i^{Sy^*} = \dfrac{\beta_i}{\sigma_{y^*}}$, which can be interpreted as meaning that for a unit increase in x_i, y^* is expected to increase by $\beta_i^{Sy^*}$ standard deviations, holding all other variables constant.

The estimated coefficients β measure the impact of a change in the explanatory variables on the unobserved order aggressiveness, y^*. To identify the direct impact of a change in the explanatory variables on the observed dependent variable, *y*, I compute the marginal effects by differentiating the conditional probabilities with respect to the explanatory variables. For buy orders, the marginal effects are:

$$\frac{\partial \Pr(y=j)}{\partial x_{ik}}\Big|(x_{i6}=0) = -\phi(\beta' x_i - \alpha_1)\beta_k\Big|(x_{i6}=0) \qquad \text{for } j=0;\ 1 \le \mathrm{k} \le 5$$

$$\frac{\partial \Pr(y=j)}{\partial x_i}\Big|(x_{i6}=0) = [\phi(\beta' x_i - \alpha_j) - \phi(\beta' x_i - \alpha_{j+1})]\beta_k\Big|(x_{i6}=0) \qquad \text{for } 1 \le \mathrm{j} \le 3;\ 1 \le \mathrm{k} \le 5$$

$$\frac{\partial \Pr(y=j)}{\partial x_i}\Big|(x_{i6}=0) = \phi(\alpha_7 - \beta' x_i)\beta_k\Big|(x_{i6}=0) \qquad \text{for } \mathrm{j}=4;\ 1 \le \mathrm{k} \le 5$$

For sell orders, the marginal effects are:

$$\frac{\partial \Pr(y=j)}{\partial x_{ik}}\Big|(x_{i6}=1) = -\phi(\beta' x_i - \alpha_1)(\beta_k + \beta_{k+6})\Big|(x_{i6}=1) \qquad \text{for } j=0;\ 1 \le \mathrm{k} \le 5$$

$$\frac{\partial \Pr(y=j)}{\partial x_i}\Big|(x_{i6}=1) = [\phi(\beta' x_i - \alpha_j) - \phi(\beta' x_i - \alpha_{j+1})](\beta_k + \beta_{k+6})\Big|(x_{i6}=1) \qquad \text{for } 1 \le \mathrm{j} \le 3;\ 1 \le \mathrm{k} \le 5$$

$$\frac{\partial \Pr(y=j)}{\partial x_i}\Big|(x_{i6}=1) = \phi(\alpha_7 - \beta' x_i)(\beta_k + \beta_{k+6})\Big|(x_{i6}=1) \qquad \text{for } \mathrm{j}=4;\ 1 \le \mathrm{k} \le 5$$

The marginal effects are continuous functions of the coefficients β and they do not involve the number of observations: it is thus possible to show that they are asymptotically normally distributed and to compute their asymptotic covariance by using the delta-method. I use the asymptotic

covariance computed through the delta-method to estimate the standard errors. I then construct a *z*-test to test the hypothesis that the marginal effects are equal to zero. The marginal effects are computed in correspondence with the mean values of the explanatory variables.

Comparing different models

I consider five measures to compare the different models estimated.

(1) Wald test for the null hypothesis that all the coefficients are equal to zero – It is the standard way of assessing the reliability of ordered probit models.

(2) Wald test for the null hypothesis that the coefficients related to unexpected earnings are equal to zero ($\beta_1 = \beta_7 = 0$) – I use it to directly test whether adding unexpected earnings to the simple model contributes to explaining changes in order aggressiveness.

(3) McKelvey and Zavoina's R^2 - It is defined as: $R^2{}_{M\&Z} = \frac{\hat{V}ar(\hat{y}^*)}{\hat{V}ar(y^*)} = \frac{\hat{V}ar(\hat{y}^*)}{\hat{V}ar(\hat{y}^*) + Var(\varepsilon)}$. Hagle and Mitchell (1992) and Windmeijer (1995) compare different pseudo-R^2 for ordinal outcomes and find that the McKelvey and Zavoina's R^2 provides the closest approximation to the R^2 obtained by a linear regression model fit on the latent variable.

(4) BIC' – It is defined as: $BIC' = -LRT + p \log n$; where *LRT* is the likelihood ratio to test that all the coefficients are equal to zero, *p* is the corresponding number of degrees of freedom, *n* is the number of observations. Raftery (1995) proposes to use the Bayesian Information Criterion (BIC) and its modification, BIC', to compare nested and non-nested models. He also shows that, across any two models, the difference in BIC is equal to the difference in BIC'. I use BIC' for computation convenience.

(5) $R^2{}_{ord}$ - It is a measure of fit that I derive by comparing predicted probabilities from the ordered probit and actual frequencies of the different categories of order aggressiveness. I define the

measure as: $R^2_{ord} = 1 - [5 - \sum_{i=1}^{5} E(\hat{p}_{i-1} \mid y = i-1)]/5$; where $\hat{p}_i$ refers to the predicted probability of outcome *i*. $R^2{}_{ord}$ ranges from zero (if predictions are all wrong) to one (if predictions are all correct).

5. Results

5.1 Ordered probit results

Table 3 shows the results of the estimation of the ordered probit. To describe the results it is helpful to write the extended form of model with unobserved order aggressiveness (*) as the dependent variable:

aggressiveness*= β_1(|unexpected earnings|)+ β_2(spread)+ β_3(depth bid)+ β_4(depth ask)+

+ β_5(volatility)+ β_6(*DS*)+ β_7(*DS*$\times$(|unexpected earnings|))+ β_8(*DS*$\times$(spread))+

+ β_9(*DS*$\times$(depth bid))+ β_{10}(*DS*$\times$(depth ask))+ β_{11}(*DS*$\times$(volatility))+ ε.

Notice that type 0 refers to the most aggressive order and type 4 refers to the least aggressive order: therefore a positive (negative) sign of the coefficient indicates a negative (positive) relation with unobserved order aggressiveness. The estimates are qualitatively analogous under the three specifications. The effect of |unexpected earnings| on aggressiveness is measured by β_1, which is negative, as expected by hypotheses 1 and 2. β_7, the coefficient which measures the incremental impact of |unexpected earnings| on the aggressiveness of sell orders, is not significantly different from zero. The marginal effects, shown in Panel B[38], confirm that a positive relation between |unexpected earnings| and order aggressiveness exists: they are positive for types 0, 1 and 2 and they are negative for types 3 and 4[39]. The results suggest that the information contained in earnings

[38] Estimated predicted probabilities are also presented in Panel C.

[39] The marginal effects presented in Panel B are computed with the control variables taking values equal to their mean values. I also computed the marginal effects corresponding to percentiles 25 and 75 of the control variables. For all the permutations I again found that marginal effects of |unexpected earnings| are positive for types 0, 1 and 2 and they are negative for types 3 and 4; moreover, they are all significantly different from zero (at a maximum level of 10%).

contributes to explaining the variation in traders' strategies. There is no evidence indicating a difference in the response of buyers and sellers to the release of information.

As far as the control variables are concerned, the estimated coefficients and the marginal effects have the expected signs for spread, depth bid and depth ask. Order aggressiveness is negatively related to the spread (β_2 and ($\beta_2 + \beta_8$) are positive, the marginal effects are negative for categories 0 to 2 and positive for categories 3 and 4), positively related to the depth on the same side of the market (β_3 and ($\beta_3 + \beta_9$) are negative, the marginal effects are positive for categories 0 to 2 and negative for categories 3 and 4), and negatively related to the depth on the opposite side of the market (β_4 and ($\beta_4 + \beta_{10}$) are positive, the marginal effects are negative for categories 0 to 2 and positive for categories 3 and 4). Volatility does not have a significant effect on order aggressiveness (β_5 and β_{11} and the marginal effects of volatility on order aggressiveness are not significantly different from zero); yet, both theoretical and empirical literature provide contradictory results regarding the effect of volatility on traders' strategies.

Panel D presents five measures to compare the full model and a simple model where unexpected earnings are not included among the explanatory variables. Because there are some quarterly earnings in the dataset provided by Datastream which are missing, the specification where unexpected earnings are measured by standardized unexpected earnings is estimated with fewer observations than the other specifications. Therefore, the full model where unexpected earnings is measured by standardized unexpected earnings should be compared to a simple model estimated by using the same observations (specification *S'* in the table). For all the models, the Wald tests allow the rejection of the hypothesis that all coefficients are equal to zero and the hypothesis that the coefficients related to unexpected earnings are equal to zero. Under specifications 1 and 2, the McKelvey and Zavoina's R^2 is greater for the full model than for the simple model. Under all the three specifications, the R^2_{ord} and the BIC' indicate an improvement in the goodness of fit of the full model with respect to the simple model.

I implemented the following two extensions of the analysis as a robustness check (the results, summarized in table 7, are qualitatively analogous to the ones described):

1. SEPARATE MODELS - I repeated the analysis separately for the buy side and the sell side of the market by estimating two different models for buy and sell orders. This approach allows me to obtain a greater explanatory power of the models but it does not allow me to directly test for differences in the response of buy and sell orders. In the separate models for the two sides of the market, aggressiveness is related only to unexpected earnings and to the control variables (following the notation of the previous section, $x_i = [x_{i1} \ldots x_{i5}]$). The marginal effects for both buy and sell orders are:

$$\frac{\partial \Pr(y = j)}{\partial x_{ik}} = -\phi(\beta' x_i - \alpha_1)\beta_k \qquad \text{for } j = 0;\ 1 \le \mathrm{k} \le 5$$

$$\frac{\partial \Pr(y = j)}{\partial x_i} = [\phi(\beta' x_i - \alpha_j) - \phi(\beta' x_i - \alpha_{j+1})]\beta_k \qquad \text{for } 1 \le \mathrm{j} \le 3;\ 1 \le \mathrm{k} \le 5$$

$$\frac{\partial \Pr(y = j)}{\partial x_i} = \phi(\alpha_7 - \beta' x_i)\beta_k \qquad \text{for } \mathrm{j} = 4;\ 1 \le \mathrm{k} \le 5$$

2. DIFFERENT CLASSIFICATION OF ORDERS – I reestimated the models with a different classification of the orders. I split type 0 orders into three types. On the buy side, from the most to the least aggressive, the three types are: market orders to buy a quantity larger or equal to that available at the best ask with parameter ECO; limit orders to buy at a price greater or equal to the best ask a quantity larger or equal to that available at the best ask; market orders to buy a quantity larger or equal to that available at the best ask without parameter ECO. It should be remarked that market orders with parameter ECO and type 0 limit orders represent an extremely small portion (0.14% and 0.39%, respectively) of all orders. This classification results into seven categories on each side of the market.

5.2 Comparison with traditional metrics of decision usefulness

I compare the results described to the results obtained by using traditional metrics of decision usefulness. In particular, I examine how stock returns, trading volume and return volatility react to the earnings announcements considered. As in the aggressiveness analysis, I concentrate on the announcement date and on two following days.

Following the standard approach in event studies (see, for example, MacKinley, 1997, for a detailed description), I define abnormal returns (*AR*) as the difference between observed returns and the corresponding forecasts from the market model: $AR_{it} = R_{it} - (\hat{a}_i + \hat{b}_i R_{mt})$; where $\hat{a}$ and $\hat{b}$ are the estimated parameters from the market model, R_m is the return on the S&P/Mib index, R_i is the return on stock *i*. I take the 120 days before the earnings announcement as the estimation period. I focus on cumulative abnormal returns (*CAR*), defined as the sum of abnormal returns from the announcement day to two days after. Table 4 reports the results of this analysis. Consistent with the findings of previous literature, for all the three measures of unexpected earnings, firms with positive (negative) unexpected earnings experience an average positive (negative) abnormal performance. Yet, none of the returns around the announcement date are significantly different from zero. I also study the returns-earnings relation by examining earnings response coefficients (examples of influential contribution in the wide literature examining earnings response coefficients are Beaver et al. (1980), Collins and Kothari (1989) and Lev and Zarowin (1999)). I estimate the equation: $CAR_{it} = \alpha + \beta(\text{earnings surprise})_{it} + \varepsilon_{it}$. Table 5 presents the results from these models: the coefficient of unexpected earnings is positive, as expected, but it significantly differs from zero only when unexpected earnings are measured by standardized unexpected earnings.

I define abnormal trading volume and abnormal volatility as in Landsman and Maydew (2002); the two metrics are derived from Beaver (1968). Abnormal trading volume is computed as: $AVOL_{it} = (V_{it} - \overline{V}_i)/\sigma_i$; where V_{it} is trading volume of stock *i* on day *t*, standardized on the number

of outstanding shares, $\overline{V}$ and σ are the mean and the standard deviation of trading volume in the estimation period. Abnormal return volatility is obtained as: $ABVAR_{it} = u_{it}^2 / \sigma_i^2$; where u_{it} is the abnormal return from the market model for stock *i* on day *t*, σ_i^2 is the variance of the market model adjusted returns in the estimation period. For both abnormal trading volume and abnormal volatility I take the 120 days before the earnings announcement as the estimation window. As shown in table 6, when observing abnormal trading volume and abnormal volatility there is evidence of a response to the news: average abnormal trading volume is significantly different from zero on the announcement day and in the two following days; average abnormal volatility is significantly different from one on the announcement day and one day after the announcement.

To summarize, the patterns of abnormal trading volume and abnormal volatility signal a market reaction to the release of earnings, whereas, when examining stock returns, there is not a clear indication that market behavior is systematically related to earnings announcements. This is in line with the findings of Cready and Hurtt (2002), who document that volume-based metrics provide more powerful tests of market response to information disclosure than return-based metrics.

6. Conclusions

Motivated by the availability of high frequency data on orders and transactions, this work proposes to use order aggressiveness as a metric to evaluate the usefulness of accounting information. I examine the effect of unexpected earnings on order aggressiveness for firms listed on the Italian Stock Exchange limit order book. I consider the annual earnings announcements from 2003 to 2005 for the 40 stocks belonging to the S&P/MIB index. I estimate an ordered probit that relates order aggressiveness to unexpected earnings and to the market determinants of aggressiveness identified by previous literature. The main finding is that order aggressiveness increases with the absolute value of unexpected earnings. This can be interpreted as evidence that part of the information released is actually used by market participants. I also compare these results to the results obtained

by using traditional metrics of decision usefulness. The analysis of abnormal trading volume and abnormal volatility documents a significant market reaction to the information disclosure. By contrast, tests of decision usefulness based on abnormal returns do not generally allow the rejection of the hypothesis that the market does not react to the announcements.

Order aggressiveness provides a metric of the market reaction to information more primitive than measures based on stock prices and trading volume. Moreover, it reflects a larger information set than stock prices and trading volume do, and it allows segmentation of the results by characteristics of orders. These features make order aggressiveness suitable to be a complementary metric of decision usefulness.

A limitation of the approach I propose is reflected by the great amount of data required to analyze order aggressiveness (in this example there are 1,528,478 orders/observations). For example, processing high frequency data for all the firms in COMPUSTAT, which represents the benchmark sample used by a number of studies in this literature, would not be feasible. This is why I limit my analysis to 40 firms over three years. Yet, the main contribution of this work is methodological and its objective is to present an application of the new metric. It is out of its scope to study the response to earnings announcements across a large sample of stocks or over a long time period.

The method described to examine order aggressiveness in the Italian exchange can be applied to the other stock markets. The Italian exchange is a pure order driven market, as are, for example, Euronext, the Scandinavian and Baltic exchanges (that use the OMX platform), the Toronto, Shanghai and Tokyo exhanges, and the Electronic Communication Networks (which interact with the NYSE and the NASDAQ). In quote driven markets, orders received by market makers can be classified analogously. Previous works (for instance, Ellul et al., 2003 and Beber and Caglio, 2006) classify orders according to their aggressiveness in the hybrid trading structure (partly quote driven and partly order driven) of the NYSE.

In a number of applications, decision usefulness research can benefit if a metric of market reaction based on traders' strategies is employed. It is crucial to consider the informational advantage associated to examining order aggressiveness with respect to observing stock prices and trading volume. The informational advantage increases as the number of orders as a proportion of the number of contracts grows. This ratio increases when price-discovery is important and traders, before committing to contracts, submit orders in an attempt to infer information from the order book. At the extreme, order aggressiveness reflects a relatively greater information set than traditional metrics in batch auctions, where orders are grouped together and a single price is determined. Batch auctions are used in many exchanges, including the NYSE and the NASDAQ, to open or close the markets; in other exchanges, for example in a segment of Euronext, they are the sole means to trade illiquid stocks. A further area of applicaton of the metric I derive concerns the reaction of different types of traders to the information release. This is related to a recent stream of works (see: Grinblatt and Keloharju, 2000; Cohen et al., 2002; Dey and Radhakrishna, 2006; Ekholm, 2006; Vieru et al., 2006) that also consider behavioral biases as drivers of investor decisions after the news. When the research question is whether buyers and sellers react differently, observing prices and trading volume alone is not sufficient; studying the characteristics of orders submitted is a possibility to overcome this limit of traditional metrics of decision usefulness.

Table 1: Distribution of order types

This table presents, for each stock and each order type (type 0 is the most aggressive and type 7 is the least aggressive), the relative frequencies (in %). Panel A reports the frequencies of buy orders, Panel B reports the frequencies of sell orders.

Panel A: Buy orders					
Order type	0	1	2	3	4
AEM	10.37	27.93	3.94	30.58	27.18
AGL	10.57	23.57	7.97	27.15	30.75
AL	8.73	23.68	4.46	31.90	31.23
AUT	9.46	23.52	4.78	27.15	35.09
BFI	4.95	30.66	3.02	32.22	29.15
BIN	2.49	30.46	5.93	29.15	31.97
BNL	5.83	30.36	1.49	32.15	30.17
BPM	12.11	23.70	9.29	20.71	34.19
BPU	8.43	17.72	10.10	30.50	33.24
BPVN	11.10	18.27	8.75	25.31	36.58
BUL	7.79	20.15	5.96	36.14	29.97
CAP	11.26	29.24	7.41	21.14	30.95
ENEL	9.13	20.27	5.88	30.36	34.36
ENI	6.54	24.34	4.97	30.59	33.56
ES	5.43	25.50	4.91	30.88	33.28
F	6.97	24.87	6.56	32.83	28.77
FNC	9.94	18.66	8.96	22.87	39.57
FSI	11.28	17.63	8.72	24.47	37.90
FWB	13.81	17.42	6.58	26.67	35.51
G	3.03	27.45	0.36	31.43	37.73
IT	7.63	19.87	7.37	29.36	35.78
LOTT	6.08	28.60	1.38	37.31	26.64
LUX	6.43	26.88	1.54	31.73	33.42
MED	3.11	22.51	10.12	27.14	37.13
MN	2.21	30.90	4.45	31.27	31.17
MPS	3.21	32.71	10.23	20.90	32.94
MS	2.83	18.64	10.25	26.58	41.70
NTV	12.67	19.69	9.72	23.58	34.33
PC	7.65	21.51	7.05	26.45	37.34
R	12.73	27.91	6.69	23.17	29.50
RCS	12.54	23.96	4.89	26.31	32.31
SPG	13.29	17.23	9.09	26.12	34.26
SPI	3.81	28.35	4.24	30.13	33.46
SPM	3.91	20.90	9.43	24.98	40.79
SRG	5.18	24.73	7.58	27.89	34.62
STM	9.24	24.63	5.91	29.09	31.13
TIT	7.74	23.10	4.34	34.70	30.12
TRN	5.86	32.90	1.94	34.41	24.88
UC	6.30	15.78	9.21	35.12	33.59
Mean	7.73	24.00	6.29	28.73	33.24
St. dev.	3.39	4.76	2.80	4.24	3.74

Panel B: Sell orders					
Order type	0	1	2	3	4
AEM	9.12	25.23	4.16	32.30	29.20
AGL	9.73	21.26	6.40	31.81	30.80
AL	8.35	22.27	4.15	32.14	33.09
AUT	8.23	28.85	4.91	25.48	32.54
BFI	5.29	29.07	3.47	32.43	29.73
BIN	1.99	34.72	7.02	26.54	29.73
BNL	5.88	28.11	1.47	32.08	32.46
BPM	16.01	22.91	8.65	18.96	33.47
BPU	8.95	18.70	11.41	28.34	32.59
BPVN	9.62	22.62	9.44	22.58	35.73
BUL	10.40	26.12	7.53	32.33	23.61
CAP	18.09	19.47	7.08	22.31	33.04
ENEL	11.21	19.99	6.34	25.54	36.92
ENI	6.63	22.02	5.60	29.26	36.48
ES	5.06	20.45	4.61	31.40	38.48
F	12.27	21.98	6.54	32.57	26.63
FNC	11.69	18.05	8.80	22.03	39.43
FSI	10.90	17.62	8.94	26.16	36.39
FWB	14.22	22.54	8.30	27.74	27.21
G	3.32	25.45	0.33	32.64	38.26
IT	7.64	21.73	7.26	26.93	36.44
LOTT	6.37	28.64	1.54	36.70	26.75
LUX	5.83	39.79	1.47	26.39	26.52
MED	4.20	20.02	8.03	26.41	41.34
MN	2.11	31.14	5.48	32.11	29.16
MPS	4.87	26.80	10.19	22.42	35.71
MS	2.21	19.76	10.13	25.57	42.33
NTV	15.39	24.02	7.49	20.23	32.87
PC	8.57	19.82	6.99	28.01	36.62
R	13.49	25.33	6.81	23.78	30.58
RCS	11.71	26.62	4.73	27.44	29.51
SPG	12.62	18.56	9.43	23.65	35.74
SPI	5.24	22.47	3.62	32.80	35.86
SPM	5.60	17.48	8.12	24.72	44.08
SRG	4.90	20.06	6.12	29.23	39.69
STM	7.20	25.78	5.13	26.89	35.01
TIT	8.23	27.93	5.64	30.73	27.48
TRN	5.52	37.10	1.73	30.40	25.25
UC	10.96	18.51	8.88	26.70	34.95
Mean	8.45	24.08	6.26	27.84	33.38
St. Dev.	3.97	5.31	2.70	4.11	4.94

Table 2: Determinants of order aggressiveness – descriptive statistics

This table reports descriptive statistics for the determinants of order aggressiveness. Panel A presents for each stock in the sample the means of the market determinants of order aggressiveness. Spread is defined as the difference between the best ask and the best bid as a percentage of the midquote (multiplied by 100); depth is defined as the quoted depth at the best bid and ask quotes; volatility is measured by the standard deviation of the last 20 midquote returns (multiplied by 100). Panel B presents the mean and the standard deviation of unexpected earnings (*UE*) corresponding to the the three years in the sample. Unexpected earnings are measured in three different ways: the difference between released earnings and the mean of analysts' forecasts of earnings provided by I/B/E/S database (*fcst*); the yearly difference in reported earnings *(rep*); standardized unexpected earnings (*SUE*).

Panel A: Market determinants of order aggressiveness

	Buy orders				*Sell orders*			
	Spread	Depth bid	Depth ask	Volatility	Spread	Depth bid	Depth ask	Volatility
AEM	0.1228	1445.7	1412.1	0.0309	0.1241	1424.7	1335.0	0.0323
AGL	0.1144	711.2	869.4	0.0196	0.121	585.2	793.7	0.0908
AL	0.1442	1332.5	1218.6	0.035	0.1468	1212.0	1175.7	0.0353
AUT	0.0876	591.6	553.3	0.0308	0.08	582.9	545.3	0.0326
BFI	0.2113	4934.9	4683.0	0.0281	0.2088	4629.0	4598.2	0.0302
BIN	0.1637	19162.4	18717.0	0.0225	0.1677	18869.7	18997.6	0.0233
BNL	0.1802	8737.4	10865.4	0.0266	0.1694	7819.8	9236.5	0.026
BPM	0.2027	1252.7	1096.5	0.0681	0.1832	1274.9	1157.5	0.0479
BPU	0.09	401.1	418.3	0.0382	0.0872	398.8	426.0	0.0306
BPVN	0.1165	573.5	618.1	0.046	0.1235	533.0	562.1	0.034
BUL	0.1963	1070.7	909.9	0.0562	0.1883	977.4	972.7	0.0395
CAP	0.1368	10654.0	7106.3	0.0241	0.1385	10538.1	7399.2	0.0233
ENEL	0.132	20921.9	21645.8	0.014	0.1398	23371.3	23670.8	0.0138
ENI	0.0685	3737.3	4103.5	0.0124	0.0651	4316.5	4575.4	0.0128
ES	0.1874	916.1	929.3	0.0605	0.2027	968.8	1150.4	0.0526
F	0.145	4780.5	4775.6	0.0222	0.1397	5039.8	5055.8	0.0266
FNC	0.1182	15471.1	16947.0	0.0218	0.1257	15044.2	16246.8	0.0203
FSI	0.1262	162.5	212.2	0.0501	0.1639	170.6	183.8	0.0555
FWB	0.0881	57.2	98.0	0.0488	0.091	52.4	86.2	0.0176
G	0.0787	486.1	586.1	0.0214	0.0775	493.1	579.3	0.0232
IT	0.1513	307.4	286.2	0.0562	0.163	313.4	304.1	0.0743
LOTT	0.1152	90.3	123.8	0.0377	0.114	101.8	132.2	0.0671
LUX	0.1129	323.8	261.1	0.0572	0.1146	317.3	268.0	0.0213
MED	0.1994	3078.5	2960.3	0.0382	0.1913	3006.5	2901.9	0.0354
MN	0.1344	373.7	486.7	0.0424	0.1444	343.5	417.4	0.0709
MPS	0.2065	7059.3	8358.2	0.0324	0.1866	6149.8	7385.5	0.0312
MS	0.1279	1669.8	1730.7	0.0232	0.1308	1564.3	1688.2	0.0323
NTV	0.126	367.1	246.1	0.0444	0.1216	305.6	241.0	0.0535
PC	0.1489	4676.6	5651.3	0.0391	0.1465	4866.8	5790.4	0.0369
R	0.1141	501.8	576.0	0.0319	0.1177	497.4	576.1	0.0358
RCS	0.1705	966.8	813.5	0.0559	0.1595	1133.3	916.7	0.0459
SPG	0.1744	26965.4	24305.6	0.0267	0.1748	26401.8	22591.0	0.0376
SPI	0.1288	3109.3	3105.5	0.0262	0.1304	3026.5	3203.3	0.0269
SPM	0.1533	1820.3	1899.8	0.0363	0.149	2158.5	2385.7	0.0355
SRG	0.2163	21704.9	20335.2	0.0198	0.202	18717.1	17789.8	0.0281
STM	0.0816	3888.9	3968.6	0.0092	0.0813	3888.3	3891.5	0.0117
TIT	0.1306	85907.2	78502.1	0.0131	0.1407	98565.6	88514.6	0.00968
TRN	0.1131	8133.4	6968.5	0.0189	0.1178	8323.5	6936.7	0.0192
UC	0.1885	53821.3	49874.6	0.0162	0.1945	59647.8	53003.3	0.0138
Mean	0.1411	8260.7	7903.1	0.0334	0.1417	8657.2	8145.8	0.0348
St. dev.	0.0396	16462.0	15179.3	0.0149	0.0374	18457.2	16594.9	0.018

Panel B									
	Year 2002			*Year 2003*			*Year 2004*		
	UE (fcst)	UE (rep)	UE (SUE)	UE (fcst)	UE (rep)	UE (SUE)	UE (fcst)	UE (rep)	UE (SUE)
Mean	-0.2215	-0.3547	-0.3869	-0.0067	0.0883	3.3665	0.0015	0.3464	0.8951
St. dev.	0.4786	1.1365	2.1218	0.1643	0.9754	18.0569	0.2791	0.8271	2.0688

Table 3: Ordered probit relating order aggressiveness and unexpected earnings

This table presents the results of the estimation of the ordered probit model described in Section 4. A joint model is estimated for buy and sell orders. The dependent variable is order aggressiveness (type 0 is the most aggressive and type 4 is the least aggressive). The independent variables are: the quoted percentage spread, defined as the difference between the best ask and the best bid as a percentage of the midquote; the quoted depth at the best bid and the quoted depth at the best ask, both divided by 100; volatility, measured by the standard deviation of the last 20 midquote returns; a dummy variable (DS) for sell orders; unexpected earnings, measured in three different ways. In specification 1 (forecast) unexpected earnings are measured by the difference between released earnings and the mean of analysts' forecasts of earnings provided by I/B/E/S database; in specification 2 (reported), unexpected earnings are measured by the yearly difference in reported earnings; in specification 3 (SUE) unexpected earnings are measured by standardized unexpected earnings. Panel A reports the estimated coefficients, the corresponding standard errors (in parentheses), the standardized coefficients and the Wald test for the null hypothesis that all the coefficients are zero. Panel B reports the marginal effects and the corresponding standard errors (in parentheses). Panel C compares predicted probabilities computed for five different percentiles (min, 20%, 40%, 60%, 80%, max) of the measures of unexpected earnings. Panel D presents model selection statistics to compare the model relating order aggressiveness and unexpected earnings to a model relating order aggressiveness to the control variables only. Specification S refers to the simple model relating order aggressiveness to the control variables only; specification S' refers to the simple model relating order aggressiveness to the control variables only and estimated using the same sample used to compute standardized unexpected earnings. The statistics presented are: the BIC'; the McKelvey and Zavoina's R-squared (R-squared-M&Z); the Wald test for the null hypothesis that all the coefficients are zero; the ordinal R-squared (R-squared-ord) as defined in Section 4; the Wald test for the null hypothesis that the coefficients related to unexpected earnings are zero. Cluster-adjusted standard errors are reported in brackets. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Estimated and standardized cofficients

	Estimated coefficients			*Standardized coefficients*		
Specification	1	2	3	1	2	3
Spread	57.435***	56.8496***	58.9336***	57.0679	56.5281	58.607
	(14.5245)	(14.8366)	(17.4718)			
Depth bid	-0.0021***	-0.0021***	-0.0018**	-0.0022	-0.0021	-0.0018
	(0.0008)	(0.0008)	(0.0007)			
Depth ask	0.0039***	0.0039***	0.0037***	0.0039	0.004	0.0037
	(0.0011)	(0.0011)	(0.001)			
Volatility	-0.126	-0.1237	-0.1560	-0.1252	-0.123	-0.1552
	(0.2294)	(0.231)	(0.2532)			
|Unexpected earnings|	-0.1564***			-0.1555		
(forecast)	(0.0489)					
|Unexpected earnings|		-0.0318**			-0.0316	
(reported)		(0.0131)				
|Unexpected earnings|			-0.0021***			-0.0022
(SUE)			(0.0006)			
DS	0.0074	0.0087	0.0018	0.0074	0.0087	0.0018
	(0.0194)	(0.0186)	(0.0191)			
(Spread)*DS	5.1366	4.8779	9.5498	5.1038	4.8504	9.4969
	(11.38)	(11.3526)	(13.0599)			
(Depth bid)*DS	0.0046***	0.0045***	0.0041***	0.0046	0.0046	0.0041
	(0.0016)	(0.0016)	(0.0014)			
(Depth ask)*DS	-0.0058***	-0.0058***	-0.0053***	-0.0059	-0.0059	-0.0053
	(0.0017)	(0.0017)	(0.0015)			
(Volatility)*DS	-0.2387	-0.2508	-0.1401	-0.2373	-0.2495	-0.1394
	(0.2692)	(0.2714)	(0.2872)			
(|Unexpected earnings|)*DS	0.008			0.008		
(forecast)	(0.0315)					
(|Unexpected earnings|)*DS		-0.0007			-0.0007	
(reported)		(0.0072)				
(|Unexpected earnings|)*DS			0.0004			0.0004
(SUE)			(0.0003)			
Wald test (11 df)	49.02***	38.62***	39.25***			

Panel B1: Marginal effects – Buy orders					
Specification 1: unexpected earnings (forecast)					
Type of order	Spread	Depth bid	Depth ask	Volatility	Unexp. Earnings
0	-7.5660***	0.0287***	-0.0515***	0.0165	2.0610***
	(1.9831)	(0.0109)	(0.0151)	(0.0301)	(0.6659)
1	-12.9935***	0.0494***	-0.0885***	0.0285	3.5394***
	(3.2881)	(0.0187)	(0.0255)	(0.0520)	(1.0969)
2	-1.2789***	0.0048***	-0.0087***	0.0028	0.3483***
	(0.3579)	(0.0018)	(0.0025)	(0.0051)	(0.1205)
3	0.9365***	-0.0035**	0.0063***	-0.0020	-0.2551**
	(0.3611)	(0.0015)	(0.0021)	(0.0037)	(0.1008)
4	20.9019***	-0.0795***	0.1425***	-0.0458	-5.6937***
	(5.2783)	(0.0299)	(0.0413)	(0.0835)	(1.7894)
Specification 2: unexpected earnings (reported)					
Type of order	Spread	Depth bid	Depth ask	Volatility	Unexp. Earnings
0	-7.5660***	0.0287***	-0.0515***	0.0165	2.0610***
	(1.9831)	(0.0109)	(0.0151)	(0.0301)	(0.6659)
1	-12.9935***	0.0494***	-0.0885***	0.0285	3.5394***
	(3.2881)	(0.0187)	(0.0255)	(0.0520)	(1.0969)
2	-1.2789***	0.0048***	-0.0087***	0.0028	0.3483***
	(0.3579)	(0.0018)	(0.0025)	(0.0051)	(0.1205)
3	0.9365***	-0.0035**	0.0063***	-0.0020	-0.2551**
	(0.3611)	(0.0015)	(0.0021)	(0.0037)	(0.1008)
4	20.9019***	-0.0795***	0.1425***	-0.0458	-5.6937***
	(5.2783)	(0.0299)	(0.0413)	(0.0835)	(1.7894)
Specification 3: unexpected earnings (SUE)					
Type of order	Spread	Depth bid	Depth ask	Volatility	Unexp. Earnings
0	-7.4972***	0.0281***	-0.0524***	0.0163	0.4195**
	(2.0336)	(0.0106)	(0.0153)	(0.0303)	(0.1779)
1	-12.8494***	0.0482***	-0.0899***	0.0279	0.7190**
	(3.3543)	(0.0183)	(0.0258)	(0.0523)	(0.2942)
2	-1.266***	0.0047***	-0.0088***	0.0027	0.0708**
	(0.3637)	(0.0017)	(0.0026)	(0.0051)	(0.0308)
3	0.9159**	-0.0034**	0.0064***	-0.0019	-0.0512**
	(0.3706)	(0.0014)	(0.0021)	(0.0037)	(0.0256)
4	20.6966***	-0.0776***	0.1448***	-0.0451	-1.1581**
	(5.3897)	(0.0294)	(0.0417)	(0.0841)	(0.4784)

Panel B2: Marginal effects – Sell orders					
Specification 1: unexpected earnings (forecast)					
Type of order	Spread	Depth bid	Depth ask	Volatility	Unexp. earnings
0	-8.1854***	-0.0316***	0.0258**	0.0477*	1.9409***
	(2.1555)	(0.0108)	(0.0106)	(0.0261)	(0.6970)
1	-14.1638***	-0.0547***	0.0447**	0.0825*	3.3586***
	(3.7159)	(0.0185)	(0.0183)	(0.0461)	(1.1334)
2	-1.4075***	-0.0054***	0.0044***	0.0082*	0.3337***
	(0.41907)	(0.0018)	(0.0017)	(0.0045)	(0.1270)
3	0.9401***	0.0036**	-0.0029**	-0.0054*	-0.2229**
	(0.3607)	(0.0015)	(0.0014)	(0.0032)	(0.1008)
4	22.8167***	0.0881***	-0.0720**	-0.1330*	-5.4104***
	(5.9690)	(0.0298)	(0.0293)	(0.0737)	(1.8657)
Specification 2: unexpected earnings (reported)					
Type of order	Spread	Depth bid	Depth ask	Volatility	Unexp. earnings
0	-8.0968***	-0.0323***	0.0251**	0.0491*	0.427**
	(2.2247)	(0.011)	(0.0105)	(0.0263)	(0.2076)
1	-13.9583***	-0.0557***	0.0433**	0.0847*	0.7361**
	(3.8263)	(0.0187)	(0.0182)	(0.0462)	(0.3434)
2	-1.3855***	-0.0055***	0.0043**	0.0084*	0.073**
	(0.428)	(0.0018)	(0.0017)	(0.0045)	(0.0364)
3	0.9335**	0.0037**	-0.0029**	-0.0056*	-0.0492*
	(0.3668)	(0.0015)	(0.0014)	(0.0033)	(0.0276)
4	22.5071***	0.0898***	-0.0698**	-0.1365*	-1.187**
	(6.151)	(0.0302)	(0.0291)	(0.0739)	(0.5613)
Specification 3: unexpected earnings (SUE)					
Type of order	Spread	Depth bid	Depth ask	Volatility	Unexp. Earnings
0	-9.024***	-0.0303***	0.0209**	0.039	0.0233***
	(2.7909)	(0.0103)	(0.0092)	(0.0273)	(0.007)
1	-15.4333***	-0.0519***	0.0358**	0.0667	0.0398***
	(4.7867)	(0.0175)	(0.0161)	(0.0471)	(0.0121)
2	-1.5999***	-0.0053***	0.0037**	0.0069	0.0041***
	(0.5613)	(0.0018)	(0.0016)	(0.0049)	(0.0014)
3	1.16***	0.0039***	-0.0027**	-0.005	-0.003***
	(0.439)	(0.0015)	(0.0013)	(0.0037)	(0.001)
4	24.8973***	0.0837***	-0.0578**	-0.1076	-0.0642***
	(7.7341)	(0.0281)	(0.0256)	(0.0757)	(0.0197)

Panel C1: Predicted probabilities for buy orders						
Specification 1: unexpected earnings (forecast)						
Type of order	Min	20%	40%	60%	80%	Max
0	6.47	6.49	6.55	6.63	6.80	6.87
1	24.62	24.66	24.76	24.91	25.19	25.32
2	5.69	5.69	5.71	5.72	5.75	5.76
3	28.80	28.80	28.79	28.78	28.77	28.76
4	34.42	34.36	34.19	33.96	33.50	33.28
Specification 2: unexpected earnings (reported)						
Type of order	Min	20%	40%	60%	80%	Max
0	6.65	6.77	6.69	6.74	6.85	9.17
1	24.90	25.11	24.97	25.06	25.24	28.72
2	5.72	5.74	5.72	5.73	5.75	6.03
3	28.77	28.76	28.76	28.76	28.75	28.16
4	33.96	33.63	33.85	33.71	33.41	27.92
Specification 3: unexpected earnings (SUE)						
Type of order	Min	20%	40%	60%	80%	Max
0	6.85	6.85	6.86	6.88	6.91	10.24
1	25.09	25.10	25.12	25.15	25.20	29.89
2	6.02	6.02	6.02	6.03	6.03	6.40
3	28.76	28.76	28.76	28.76	28.75	27.74
4	33.28	33.27	33.24	33.19	33.10	25.74

Panel C2: Predicted probabilities for sell orders						
Specification 1: unexpected earnings (forecast)						
Type of order	Min	20%	40%	60%	80%	Max
0	6.39	6.41	6.47	6.55	6.71	6.87
1	24.47	24.51	24.61	24.75	25.04	25.32
2	5.67	5.68	5.69	5.70	5.73	5.76
3	28.80	28.80	28.80	28.79	28.78	28.76
4	34.66	34.61	34.43	34.20	33.74	33.28
Specification 2: unexpected earnings (reported)						
Type of order	Min	20%	40%	60%	80%	Max
0	6.58	6.70	6.62	6.67	6.77	9.17
1	24.77	24.98	24.84	24.93	25.11	28.72
2	5.70	5.72	5.71	5.72	5.74	6.03
3	28.78	28.76	28.77	28.77	28.76	28.16
4	34.17	33.84	34.06	33.92	33.62	27.92
Specification 3: unexpected earnings (SUE)						
Type of order	Min	20%	40%	60%	80%	Max
0	6.76	6.76	6.77	6.79	6.82	10.24
1	24.94	24.94	24.97	25.00	25.05	29.89
2	6.00	6.00	6.01	6.01	6.02	6.40
3	28.77	28.77	28.77	28.77	28.76	27.74
4	33.53	33.52	33.48	33.43	33.35	25.74

Panel D: Full model (with unexpected earnings) vs. Simple model (only market regressors)					
	Full model			*Simple model*	
Specification	1	2	3	S	S’
BIC'	-16156.486	-14204.338	-11342.445	-12994.058	-11070.177
R-squared-M&Z	0.013	0.011	0.011	0.010	0.011
R-squared-ord	0.20205244	0.20178411	0.20173308	0.20160831	0.20156505
Wald (11df/9df)	49.02***	38.62***	39.25***		
Wald *ue* (2df)	10.56***	5.88*	12.00***		

Table 4: Cumulative abnormal returns and unexpected earnings

This table reports average cumulative abnormal returns, as defined in Section 5, from the earnings announcement day to 2 days after (day 0 corresponds to the earnings announcement day). The returns are compared under negative and positive unexpected earnings. Unexpected earnings are measured in three different ways: the difference between released earnings and the mean of analysts' forecasts of earnings provided by I/B/E/S database (*UE – forecast*); the yearly difference in reported earnings *(UE – reported*); standardized unexpected earnings (*UE – SUE*). *T*-tests for the null hypothesis that the average returns are equal to zero are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Day	*UE - forecast*		*UE – reported*		*UE – SUE*	
	>0	<0	>0	<0	>0	<0
0	0.0002	0.0007	0.0004	0.0010	-0.0003	0.0007
	(0.0989)	(0.3255)	(0.2419)	(0.2708)	(-0.2995)	(0.2047)
1	0.0019	0.0005	0.0022	-0.0013	0.0016	-0.0043
	(0.7288)	(0.1320)	(1.0855)	(-0.1865)	(0.8912)	(-0.9839)
2	0.0031	-0.0004	0.0024	-0.0022	0.0020	-0.0053
	(0.8924)	(-0.0879)	(0.9459)	(-0.2707)	(0.8377)	(-1.0735)

Table 5: Linear model relating cumulative abnormal returns and unexpected earnings

This table presents the results of the estimation of a linear model relating cumulative abnormal returns and unexpected earnings. The dependent variable is the cumulative abnormal return, defined as in Section 5, computed over the period [0,2] days from the earnings announcement. Unexpected earnings are measured in three ways: in specification 1 (forecast) unexpected earnings are measured by the difference between released earnings and the mean of analysts' forecasts of earnings provided by I/B/E/S database; in specification 2 (reported), unexpected earnings are measured by the yearly difference in reported earnings; in specification 3 (SUE) unexpected earnings are measured by standardized unexpected earnings. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Specification	1	2	3
Constant	0.0012	0.0009	-0.0015
	(0.0029)	(0.0028)	(0.0024)
Unexp. earnings	0.0018		
(forecast)	(0.0094)		
Unexp. earnings		0.0025	
(reported)		(0.0027)	
Unexp. earnings			0.0028**
(SUE)			(0.0012)
R-squared	0.0005	0.0093	0.0660

Table 6: Abnormal volatility and abnormal volume over time

This table reports the mean abnormal variance and the mean abnormal volume, defined as in Section 5, from the earnings announcement day to 2 days after (day 0 corresponds to the earnings announcement day). *T*-tests for the null hypothesis that the average abnormal volatility is equal to one or the average abnormal volume is equal to zero are presented in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Day	*Abnormal volatility*	*Abnormal volume*
0	1.7371**	0.8619***
	(2.311)	(6.0227)
1	2.2097***	1.0079***
	(3.1953)	(7.5185)
2	1.1817	0.4591***
	(0.7841)	(3.3026)

Table 7: Orderd probit analysis - robustness checks

This table summarizes two extensions of the ordered probit analysis (as described in Section 5). Panel A reports the coefficients related to unexpected earnings (with standard errors in parentheses) when separate models for buy and sell orders are estimated. Panel B reports the coefficients related to unexpected earnings (with standard errors in parentheses) when order aggressiveness is classified into seven categories. Unexpected earnings are measured in three different ways: the difference between released earnings and the mean of analysts' forecasts of earnings provided by I/B/E/S database (*UE – forecast*); the yearly difference in reported earnings *(UE – reported*); standardized unexpected earnings (*UE – SUE*). ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Separate models for buy and sell orders			
	UE - forecast	*UE – reported*	*UE – SUE*
|Unexpected earnings|	-0.1571***	-0.0319**	-0.0022***
(buy model)	(0.0491)	(0.0131)	(0.0006)
|Unexpected earnings|	-0.1477***	-0.0324**	-0.0017***
(sell model)	(0.0507)	(0.0152)	(0.0005)

Panel B: Aggressivenss classified into 7 categories			
	UE – forecast	*UE – reported*	*UE – SUE*
|Unexpected earnings|	-.01523***	-0.0310**	-0.0021***
	(0.0478)	(0.0127)	(0.0006)
|Unexpected earnings|*DS	0.0086	-0.0004	0.0004
	(0.0312)	(0.0071)	(0.0003)

Figure 1: The aggressiveness classification – examples

This figure presents examples of buy orders for each category of aggressiveness. 'Market' refers to a market order; 'limit' refers to a limit order; the arrows indicate the quotes against which market and marketable limit orders are executed or the position in the book where limit orders are placed. On the buy side, the following five categories of orders are defined, corresponding to decreasing degrees of aggressiveness. *Type 0*: market orders to buy a quantity larger or equal to that available at the best ask (with or without parameter ECO); limit orders to buy at a price greater or equal to the best ask a quantity larger or equal to that available at the best ask. *Type 1*: market orders to buy a quantity lower than that offered at the best ask; limit orders to buy at a price higher or equal to the best ask a quantity lower than that available at the best ask. *Type 2*: limit orders to buy at a price greater than the best bid and lower than the best ask. *Type 3*: limit orders to buy at a price equal to the best bid. *Type 4*: limit orders to buy at a price lower than the best bid. On the sell side, orders are defined symmetrically.

Type 0

a. market (ECO) # 400
(totally executed)
c. market # 400
(partially executed,
a limit at 101 # 260 is then placed)

Ask	
Price	*Quantity*
103	100
102	200
101	140

b. limit at 102 # 400
(partially executed,
a limit at 102 # 60
is then placed)

Type 1

a. market # 100
(totally executed)

Ask	
Price	*Quantity*
103	100
102	200
101	140

b. limit at 102 # 100
(totally executed)

Type 2

limit at 99 # 100
(limit placed
as the best bid at 99)

Bid		*Ask*	
Quantity	*Price*	*Price*	*Quantity*
		103	100
110	98	102	200
200	97	101	140

Type 3

limit at 98 # 100
(limit placed
in the queue at 98)

Bid		*Ask*	
Quantity	*Price*	*Price*	*Quantity*
		103	100
110	98	102	200
200	97	101	140

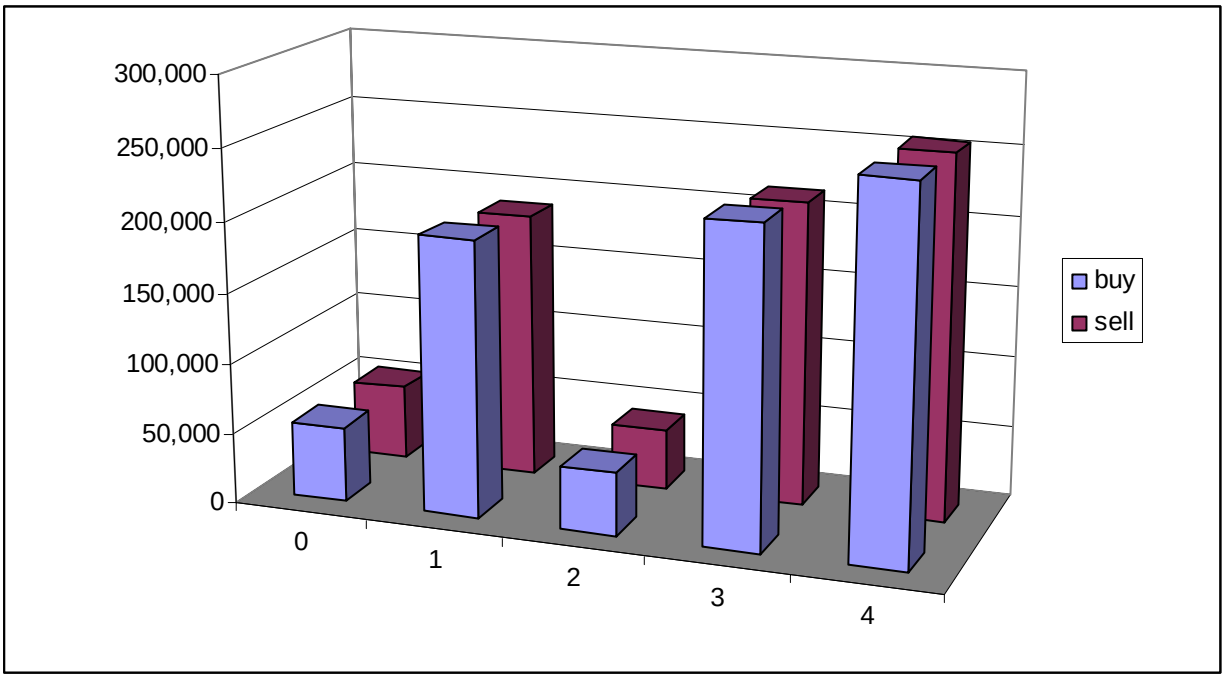
Type 4

limit at 95 # 100
(limit placed
in the queue at 95)

Bid		*Ask*	
Quantity	*Price*	*Price*	*Quantity*
110	98	103	100
200	97	102	200
		101	140

Figure 2: Distribution of order types

This figure compares the absolute frequency (*y*-axis) of each type of order (*x* axis). Type 0 is the most aggressive and type 4 is the least aggressive order.



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PART 2

MARKET MAKERS AS INFORMATION PROVIDERS: THE NATURAL EXPERIMENT OF STAR

This part of the thesis presents an empirical investigation on the activity of specialists interacting with a limit order book[40]. I examine the effect of the introduction of specialists with information disclosure requirements in STAR, a segment of the Italian equity market dedicated to small-medium firms. I find that spreads and volatility decrease after firms enter in the new segment. The results can be explained by a decrease in information asymmetries and, thus, in adverse selection costs, following the introduction of the specialists. This work contributes to previous literature on the design of hybrid markets and on the economic consequences of disclosure in that it is the first to examine the role of specialists as information providers.

[40] The results of the analysis will be discussed in a paper coauthored by my thesis advisor, Barbara Rindi.

1. Introduction

Enhancing market quality for less traded stocks is an issue that ranks high in regulators' agenda. Some markets (for example Euronext, OMX, the Italian Stock Exchange) have recently tackled the problem by introducing market makers (also termed specialists), who are required to maintain regular presence during the trading process. This work studies the effect of the introduction of specialists on market quality by concentrating on their role as information providers.

In April 2001, the Italian Stock Exchange (Borsa Italiana, BIt from now on) introduced in its limit order book a new segment of trading, named STAR, dedicated to stocks with small-medium capitalization. Stocks belonging to STAR are assigned a market maker with obligations in terms of liquidity and information disclosure. Liquidity obligations concern a maximum quoted spread, a minimum quote size and a minimum trading volume. As for information disclosure, specialists are required to produce at least two detailed financial analyses each year, and to organize, together with BIt, at least two meetings -still per year- with professional investors; during these meetings, named roadshows, specialists are required to present a report on the companies' economic and financial perspectives. The purpose of the analysis is to study how these information disclosure requirements affect market quality.

Previous empirical works on the activity of specialists in order driven markets do not consider this important aspect of market making as other existing market makers do not have obligations regarding information disclosure; they generally have only liquidity requirements, the most relevant being the maximum quoted spread. In the Italian case, instead, for the 59 companies that entered into STAR between 2001 and 2005, the maximum spread requirement was not binding, and this created an ideal setting to focus on the effect of information disclosure provided by market markers. Moreover, the Italian experiment took place in the absence of microstructure confounding effects as no change in the market structure occurred when these stocks were assigned a specialist.

I use high frequency data covering 32 months around the entrance of each stock in STAR. I find that immediately after the assignment of the specialist, spread and volatility decrease for STAR stocks compared to a matched sample of control stocks. Volume, instead, does not change significantly in the period immediately after. In the longer run, I find that spread and volatility decrease substantially and volume increases significantly. This improvement in market quality can be explained by a decrease in information asymmetries (and, in turn, in adverse selection costs) brought about by STAR's information disclosure requirements. Following Easley et al. (1996), I estimate the probability of informed trading (PIN); I find that information asymmetries, measured by PIN, significantly decrease when companies enter into STAR. This is consistent with any model of price formation with asymmetric information and rational agents (e.g. Grossman and Stiglitz (1980)), where private information is disclosed to uninformed market participants. When informed traders act as liquidity providers, which is the case of order driven markets, if uninformed agents become more informed, their adverse selection costs decrease and they become more willing to supply liquidity, thus reducing the price impact and the spread.

This analysis is closely related to previous empirical works on the effects of the introduction of specialists on market quality[41]. Venkataraman and Waisburd (2006) find that introducing specialists in the Paris Bourse led to an increase in liquidity for a sample of stocks traded through a call auction. Anand et al. (2006) document an improvement in market quality after the introduction of specialists in the limit order book of the Stockholm Stock Exchange; in this case, however, specialists were required to quote spreads lower than the ones prevailing before their introduction and they had no obligations in terms of information disclosure. Menkveld (2006) finds that liquidity

[41] A theoretical literature also examines the role of specialists in providing liquidity and on how they compete with limit order books; these models are not generally able to give clear cut predictions regarding the effect of introducing specialists on market quality. Moreover, they do not consider the role of specialists as uninformed competitive liquidity providers. Grossman and Miller (1988) show that specialists can increase liquidity by reducing temporary imbalances in the order flow. In the model of Seppi (1997) it is shown that a hybrid market structure (with a limit order book and specialists) can provide better liquidity than a pure limit order book depending on the order size, whereas Parlour and Seppi (2002) identify conditions under which a hybrid market structure Pareto-dominates a pure limit order book. Finally, Viswanathan and Wang (2002) show that introducing specialists in a limit order book can improve the welfare of customers.

is increasing in the number of designated market makers in Euronext. Finally, Nimalendran and Petrella (2003) study the transitory introduction (from 1997 to 1999) in BIt of a market segment, designed for infrequently traded stocks, with a limit order book and specialists; they observe that stocks belonging to the new segment experienced an increase in liquidity; this work differs as I concentrate on information disclosure rather than on mere liquidity provision.

The results of this analysis also contribute to the empirical research on the economic consequences of disclosure. Surveys of this wide literature are contained in Core (2001), Healy and Palepu (2001) and Leuz and Wysocki (2007). Most studies examine the costs and benefits associated with managers' voluntary disclosure choices. Other works consider the effect of changes in disclosure regulation; among those, a growing number of articles are concerned with the introduction of IFRS. Leuz and Verrecchia (2000) point out that, when employing data from an already rich environment, like the US market, on which much of prior evidence is based, problems arise in evaluating the effect of disclosure; conversely, STAR is dedicated to stocks with fairly limited degree of disclosure, and, thus, the analysis does not share this problem. In general, my analysis adds to this literature as I concentrate on a form of mandatory disclosure that, to my knowledge, has not been previously investigated.

The remainder of this part of the thesis is organized as follows. Section 2 describes the dataset and the sample choice; section 3 outlines the hypotheses that motivates the empirical analysis; section 4 is devoted to the results concerning market quality; section 5 comments on the results on information asymmetries and the market reaction to roadshows; section 6 concludes.

2. Dataset and samples

2.1 Institutional background: The Italian Stock Exchange and STAR stocks

STAR is a segment of trading dedicated to stocks with capitalization lower than one billion euro and that are assigned market makers with obligations in terms of liquidity and information

disclosure. STAR stocks are traded in the MTA (Mercato Telematico Azionario), the electronic limit order book of the Italian Stock Exchange; in the other segments of the electronic platform there are no specialists supporting trading.

Table 1 summarizes specialists' liquidity obligations: they are required to quote a maximum spread and to assure minimum depths and minimum trading volume; moreover they have to continuously post bid and ask quotes starting from the pre-auction phase. As for information disclosure, specialists have to produce at least two financial analyses each year, where they have to present the recent available data, expectations about future economic results and a comparison with previous estimates. All the studies and research reports have to be timely transmitted to the stock exchange. In addition, specialists have to organize at least twice per year a meeting with professional investors, which are referred to as roadshows[42].

Trading for STAR stocks takes place during four phases: an opening call auction, from 8:00am to 9:00am; a continuous trading phase, from 9:00am to 5:25pm; a closing call auction, from 5:25pm to 5:35pm; and, on a voluntary basis, an "after hours" trading phase, from 6:00pm to 8:30pm. I examine only data from the continuous auction, where both individual traders and specialists submit orders, which are then matched by a centralized mechanism according to standard price and time priority rules.

2.2 Sample stocks, control stocks and sample periods

I consider the 59 stocks that entered into STAR between April 2001 (when STAR was introduced) and February 2006, and that were previously listed on BIt. Table 2 reports the dates corresponding to the entrance in STAR. These dates are dispersed as a group of 31 stocks were assigned a specialist on four dates in 2001, one stock in 2002, another group of three stocks in 2004 and 24

[42] Specialits' obligations in terms of information disclosure are complemented by requirements for the firms. Issuers have to publish quarterly reports within 45 days after the end of each quarter. They have to transmit to the stock exchange the annual, half-yearly and quarterly financial data in an electronic format and to communicate timely possible balance sheet data changes. Finally, balance sheets, half-yearly and quarterly reports, along with the price-

stocks in 2005. The dispersion of the dates reduces the probability of observing confounding effects due to market elements not related to the specialists' activity; however, in order to control for these effects completely, I build a control sample of stocks with the same capitalization requirements as STAR stocks[43]. Following the approach proposed by Huang and Stoll (1996), each STAR stock is matched to another stock that minimizes the score: $\sum_{i=1}^{5}\left(\frac{x_i^{STAR}-x_i^{control}}{(x_i^{STAR}+x_i^{control})/2}\right)^2$; where x_i is either price, or market capitalization, or trading volume, or market-to-book ratio, or leverage.

I consider four periods around the introduction of each stock in STAR. The *pre*-STAR period goes from four to one month before the event and the *post*-STAR period goes from one to four months after the event; the *post1*-STAR and *post2*-STAR periods include the same months as the post-STAR, but one and two years ahead, respectively. In the *post* period I expect to observe the effect of the commitment to greater disclosure. I examine the *post1* and *post2* periods because I am mainly interested in the longer run effects of the specialists' activity.

BIt provided us with data on transaction prices and bid ask quotes from November 2000 to February 2006 for each STAR stock except four companies. Hence, for the pre and post periods I worked with a sample of 55 stocks; because three stocks entered into STAR in 2004 and 25 in 2005 (for some of these stocks the *post1* and *post2* periods would exceed February 2006), I ended up with a sample of 32 stocks for the *post1* and of 30 stocks for the *post2* period, respectively.

2.3 Liquidity and information disclosure requirements in the sample

Table 2 compares the average spread prevailing in the *pre* period and the maximum spread required for the specialists. For all the stocks in the sample the maximum spread is greater than the average spread in the *pre* period. If the maximum spread rule is not binding, the other main liquidity

sensitive documentation and the papers distributed during roadshows, must be all available on the company website, according to a format specifically indicated, both in Italian and in English.

[43] Control stocks are identified among the stocks belonging to Standard, a trading segment with the same capitalization requirements as STAR.

requirements (continuous quoting and minimum quote size) are also ineffective. Therefore, by comparing a period before the introduction of the specialists to a later period, I am able to focus on the effect of information disclosure requirements.

3 Empirical hypotheses

To my knowledge, a micro-financial model that discusses in detail the effect of information disclosure by liquidity providers in limit order markets does not exist. One difficulty faced by theoretical analysis is that if asymmetric information among market participants is assumed, the existing models of limit order trading do not provide a closed form solution for the equilibrium price function. Hence, the closest theoretical frameworks one could use to derive empirical predictions for an order driven electronic market are the centralized auction models in the spirit of Grossman and Stiglitz (1980). I refer to this class of models and formulate testable hypotheses regarding the effect of the introduction of specialists in STAR on market quality and on information asymmetries.

BID-ASK SPREAD - Since the early literature on asymmetric information (Kyle, 1985 and Glosten and Milgrom, 1985), it has been shown that an increase in information disclosure reduces adverse selection costs, as perceived by uninformed liquidity providers, and therefore it reduces the price impact and the bid-ask spread. An increase in information disclosure induces uninformed traders to supply cheaper liquidity as they can better screen between informed and noise traders; this is also true when liquidity providers are both informed and uninformed as in order-driven markets[44]. Overall, there seems to be a consensus around the idea that information disclosure reduces the bid-ask spread by curtailing adverse selection costs. This leads to my first hypothesis:

[44] In order driven markets, all agents, both informed and uninformed, act as liquidity providers who submit their demand function (proxy for limit orders); see, for example, Rindi (2008), where a Grossman and Stiglitz (1980) type of framework is used.

Hypothesis 1: the bid-ask spread of STAR stocks decreases following the introduction of the specialists

PRICE VOLATILITY – To examine the effect of information disclosure on price volatility I can make reference again to an auction type model of price formation, as in Brown and Zhang (1997). In such models, two effects of disclosure on volatility can be described. On the one hand, disclosure reduces adverse selection costs and reduces the price impact, which is inversely related to volatility. On the other hand, disclosure makes uninformed traders more informed and induces them to trade more aggressively (i.e. their price reaction to information increases) on the information they possess; this increases volatility[45].

The overall result of information disclosure on price volatility has to be assessed empirically as it depends on the characteristics of the market. Yet, I expect the equilibrium outcome to be substantially affected by the initial level of liquidity. In illiquid stocks, if information is disclosed, I expect that the main effect is on the price impact, which soon decreases due to the reduction in adverse selection costs. Here, there are not many uninformed traders ready to trade on new information, but rather there are careful limit order submitters who know how much insider trading can concentrate on illiquid stocks. This allows us to formulate my second hypothesis:

Hypothesis 2: price volatility of STAR stocks decreases following the introduction of the specialists

TRADING VOLUME - As said, in a stylized model in the spirit of Brown and Zhang (1997), information disclosure increases uninformed traders' aggressiveness and therefore the variance of

[45] Consider a standard model of Rational Expectations with risk averse informed and uninformed traders, and noise traders; the equilibrium price solves as a function of the fundamental value of the asset, as well as of all the unknown random variables which affect agents' trading strategies. For example, if q is the future value of the asset, s=q+e is the informed traders' noisy signal, and ϕ is a proxy for noise trading, the equilibrium price function looks like: $p = \varsigma_1 q + \varsigma_2 \phi$. Disclosure decreases ς_2 (the price impact) and increases ς_1 (the parameter that measures aggressivenes).

their demand function. If follows an increase in trading volume, proxied, as for example in Admati and Pfleiderer (1988), by the variance of the order flow. Thus, I to turn to a third hypothesis:

Hypothesis 3: trading volume of STAR stocks increases following the introduction of the specialists.

INFORMATION ASYMMETRIES – I expect to observe a reduction in information asymmetries determined by the disclosure of information brought about by the specialists. Accordingly, the class of models used to justify hypotheses 1 through 3 assumes that information disclosure reduces information asymmetries. This assumption needs to be verified empirically and, thus, I state a fourth hypothesis:

Hypothesis 4: information asymmetries for STAR stocks decrease following the introduction of the specialists

4. Empirical analysis: market quality

I focus on three measures of market quality: spread, volatility and trading volume. These measures are computed during the trading day from 11am to 4pm. I use this time interval as it was certainly not affected by the structural changes (e.g. marginal changes in trading hours and the introduction of the closing auction (Kandel et al., 2007)) which took place during the sample period under analysis.

I use two measures of spread: the percentage quoted spread and the time-weighted quoted spread. The percentage quoted spread is computed as the difference between the best ask and the best bid relative to the mid-quote. The time weighted quoted spread is computed by weighing each quoted spread observation on the time between two subsequent quotes. I use the following weighted version of the realized volatility measure proposed by Andersen et al. (2003)[46] :

[46] The formula is obtained by assuming that stock prices follow a brownian motion. In Andersen et al. (2003) volatility is not weighted on time because observations are equally distant.

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{\ln\left(\frac{p_i}{p_{i-1}}\right)^2}{\frac{(t_i - t_{i-1})}{T}}}$$

where p_i is the spread mid-quote at time *t*. The spread mid-points are used rather than transaction prices in order to control for the component of volatility that is due to the bid-ask bounce. *N* is the number of observations in the specific sample period and *T* is the number of seconds in the time interval considered. Because the dataset contains all quote revisions and, hence, the time between two subsequent observations is not constant, I weigh each observation by the duration (in seconds) between subsequent quote updates. Finally, trading volume is defined as the sum of transaction volumes (in euro) in the time interval considered.

Table 3 through 6 present descriptive statistics for the measures of market quality considered.

4.1 Measures of market quality: univariate analysis

Table 7 compares the average change in the three measures of market quality for STAR and control stocks in the different sub-periods under analysis. For each measure, *y*, I concentrate on the difference in differences, defined as $DID = [y_{STAR}(After) - y_{STAR}(\Pr e)] - [y_{Control}(After) - y_{Control}(\Pr e)]$, where *Pre* refers to observations before the introduction of STAR and *After* refers to observations after. I compute a paired-sample *t*-test and a signed-rank Wilcoxon test for the null hypothesis that the average or the median of this difference is equal to zero.

SPREAD - For the treatment stocks the average quoted spread (Panel A) and the average time-weighted quoted spread (Panel B) decrease over the three sample periods; this difference is significantly greater (in absolute value) than the difference experienced by control stocks. In addition, it should be noticed that the spread reduction is three and four times larger in the *post1* and the *post2* periods.

VOLATILITY – Volatility (Panel C) for STAR stocks decreases in the *post* and *post2* periods, whereas it increases in the *post1* period. However, volatility for STAR stocks significantly decreases across the three sample periods compared to control stocks; the reduction is smaller during the *post1* period.

TRADING VOLUME – STAR stocks exhibit a decrease in volume (Panel D) in the *post* and *post1* periods and an increase in the *post2* period. Volume increases with respect to the control sample only in the *post1* and *post2* periods, but these changes are not significantly different from zero.

The results of the univariate analysis support hypothesis 1 and 2. Conversely, hypothesis 3 cannot be confirmed by these results.

4.2 Measures of market quality: multivariate analysis

In the univariate analysis I employ one observation for each stock in each sub-period. I also consider a multivariate approach, where I use one observation for each day in the sample.

Following Venkataraman and Waisburd (2006), for each market quality measure, *y*, I estimate the following model:

$$y_{i,t} = \beta_0 + \beta_1 Control_i + \beta_2 After_{i,t} + \beta_3 (After_{i,t} * Control_i) + \varepsilon_{i,t}$$

where *Control* is a dummy for control stocks and *After* is a dummy variable which is equal to 0 during the *pre*-period and 1 during the other sample periods. The interpretation of the model coefficients is straightforward and allows us to compare changes in the market quality measures both between the treatment and the control sample, and between the period before and the periods after the introduction of the specialists. If β_1 is positive, it means that, all else equal, *y* is greater for control stocks than for STAR stocks. β_2 is positive if *y* increases for STAR stocks after the introduction of the specialists. More importantly, if β_3 is positive, the increase in the dependent variable is greater for control stocks than for STAR stocks. The model is estimated with three sets

of data, separately: for each after STAR period, *T*, I consider the comparison (*pre* vs. *T*) where I only use data from the *pre* and *T* periods. Table 8 reports the results.

SPREAD – In the models for the quoted spread (Panel A) and for the time-weighted quoted spread (Panel B), for the three period comparisons, β_2 is significant and negative, while β_3 is significant and positive. Confirming the findings of the univariate analysis, this suggests that the introduction of the specialists consistently decreases both the spread and the time-weighted spread of STAR stocks relative to that of control stocks during the three sample periods.

VOLATILITY – The results for volatility (Panel C) also confirm the univariate findings. β_2 is significant and negative in the (*pre* vs. *post*) and (*pre* vs. *post2*) comparisons, and it is negative but not significant in the (*pre* vs. *post1*) comparison. However, β_3 is significant and negative over the three period comparisons; this indicates that volatility for treatment stocks decreases more (and increases less in the *post1* period) than for control stocks.

TRADING VOLUME – Volume (Panel D) is affected by the introduction of the specialists. Right after the introduction of the specialists (a month later) the variation in volume for STAR stocks is not significantly different from that of control stocks (β_3 is not significant). This result was not unexpected as informal conversations with professionals acting as specialists on STAR stocks had advised us that it certainly takes a while for the specialists to build volume in fairly illiquid stocks, especially when the spread requirements are not binding. In the *post1* period STAR volume decreases (β_2 <0), but the reduction is not significantly different from zero, even if compared to control stocks, it shows a better performance (β_3<0 and significant). Finally, volume increases two years after the introduction of the specialists and this increase in greater than for control stocks (in the (*post1* vs. *post2*) comparison β_2>0, β_3<0, and both parameters are significantly different from zero).

To control for unobservable variables that affect market quality I also estimate the model with firm-pair fixed effects; the results, reported in Table 9, are qualitatively analogous.

The results of the multivariate analysis confirm hypothesis 1 and 2. Hypothesis 3 can be confirmed only for the *post1* and *post2* periods.

5. Empirical analysis: Information Disclosure, Asymmetric Information and Probability of Informed Trading

The results in Section 4 show that after the introduction of the specialists spread and volatility significantly decrease. As the specialists' maximum spread requirement is not binding when the stocks enter into STAR, this improvement of market quality cannot be related to the specialists' liquidity obligations. Instead, I conjecture that it is driven by the reduction of adverse selection costs induced by the information disclosure requirements. To further inquire into the effect of disclosure, I examine the market reaction to the information released in roadshows[47]. Moreover, if the conjecture is correct, as stated in hypothesis 4, I expect information asymmetries to decrease for stocks that enter into STAR. Accordingly, I study how information asymmetries, measured by the probability of informed trading, vary for STAR stocks in the four sub-periods under analysis.

5.1 Market reaction to the release of information: roadshows

Disclosure requirements for STAR stocks prescribe that specialists organize meetings, called roadshows, with professional investors. At least two roadshows per year must be held; one is generally held in Milan and the others in London or in New York. During roadshows, specialists present a detailed report on the recent performance and on the outlooks of the company. To study the relevance of the release of these reports, I analyze the market reaction to roadshows by using a standard event study approach.

[47] I do not examine the market reaction to the release of specialists' financial reports because I could not obtain the complete list of the corresponding dates from Bit.

I examine two metrics of market reaction commonly used in the literature on the usefulness of accounting information[48]: abnormal returns and abnormal trading volume. Abnormal returns (*AR*) are computed as the residuals from the market model:

$$AR_{it} = R_{it} - (\hat{a}_i + \hat{b}_i R_{mt})$$

where $\hat{a}$ and $\hat{b}$ are the estimated parameters, R_m is the return on the All STAR index, whereas R_i is the return on stock i. Because I am not able to distinguish between good and bad news, I examine an absolute response metric, *ABRET*.

Following Cready and Hurtt (2002), I define absolute abnormal returns (*ABRET*) as:

$$ABRET_{it} = [|AR_{it}| - E(|AR_i|)] / \sigma(|AR_i|)$$

where $E(|AR_i|)$ and $\sigma(|AR_i|)$ are the mean and the standard deviation of $|AR_i|$ over the estimation period, respectively.

Furthermore, I define abnormal trading volume (*AVOL*), as in a number of works that build on Beaver (1968):

$$AVOL_{it} = [V_{it} - E(V_i)] / \sigma(V_i)]$$

where V_{it} is trading volume of stock i on day t, standardized on the number of outstanding shares, and $E(V_i)$ and $\sigma(V_i)$ are the mean and the standard deviation of trading volume over the estimation period, respectively.

For the computation of both abnormal returns and abnormal trading volume I take the 345 days before the roadshows as the estimation period. I also checked for the date of the quarterly earning announcements and verified that these two disclosures do not overlap.

RESULTS – Table 10 and Figures 1 and 2 present the mean absolute abnormal returns and the mean abnormal volume around roadshows. There is a peak right around the information disclosure date, being abnormal returns significantly different from zero from day -1 to +3. The impact of

[48] See Kothari, 2001 for a critical survey of this literature.

disclosure on trading volume lasts for a wider window: abnormal volume is significantly different from zero from day -8 to +8, with the only exception of day +3. Therefore, I can interpret this result as evidence that market participants perceive the information released in the roadshows as useful.

5.2 Information Asymmetries and the Probability of Informed Trading

I measure information asymmetries by estimating the probability of informed trading (PIN) as it is derived in the model of Easley et al. (1996). This method to studying information asymmetries has been extensively used in market microstructure, corporate finance, asset pricing and financial accounting. The model considers a market for a single risky asset, where a competitive market maker receives orders from informed and uninformed traders[49]. The market game is repeated over *T* days. At the beginning of each day an information event occurs with probability α, and it is good news with probability $(1-\delta)$ and bad news with probability δ. Orders from informed traders (who know whether the event is good or bad news) and uninformed traders (who trade for liquidity reasons) follow a Poisson process with daily intensity μ and ε, respectively. The probability of observing *B* buys and *S* sells on day t, conditional on the parameters of the model ($\Theta \equiv [\mu, \varepsilon, \beta, \delta]$), can be derived as:

$$\Pr[y_t = (B,S) \mid \Theta] = \alpha(1-\delta)e^{-(\mu+2\varepsilon)} \frac{(\mu-\varepsilon)^B \varepsilon^S}{B!S!} + \alpha\delta e^{-(\mu+2\varepsilon)} \frac{(\mu+\varepsilon)^S \varepsilon^B}{B!S!} + (1-\alpha)e^{-2\varepsilon} \frac{\varepsilon^{B+S}}{B!S!}$$

where y_t contains the number of buys and sells on day *t*.

The likelihood function is then computed by assuming that $\{y_t\}_{t=1}^T$ are i.i.d. I use the reformulated log-likelihood proposed by Easley et al. (2002):

$$L(\{y_t\}_{t=1}^T \mid \Theta) = \sum_{t=1}^{T} [-2\varepsilon + M\ln(x) + (B-S)\ln(\mu+\varepsilon)] +$$

[49] The model has been applied to both quote driven and order driven markets. An example of application to order driven markets is Atkas et al. (2007), in which PIN is estimated using data from the electronic limit order book of Euronext.

$$+\sum_{t=1}^{T}\ln[\alpha(1-\delta)e^{-\mu}x^{S-M}+\alpha\delta e^{-\mu}x^{B-M}+(1-\alpha)x^{B+S-M}]$$

where M=min(B,S)+max(B,S)/2, and $x=\dfrac{\varepsilon}{\mu+\varepsilon}$.

The probability of informed trading is defined as the ratio of the arrival rate of informed orders to the arrival rate of all orders:

$$PIN=\frac{\alpha\mu}{\alpha\mu+2\varepsilon}$$

To obtain the estimate of PIN, I only need the number of buys and sells in each day in the sample[50]. To classify trades as buys or sells I use the algorithm proposed by Lee and Ready (1991). Accordingly, a trade is classified as a buy if its execution price is above the previous midquote and it is classified as a sell if its execution price is below; if the execution price is equal to the previous midquote, then it is compared to the price of the previous trade and the trade is classified as a buy (sell) if there has been an upward (downward) price change. In the comparison between the execution price and the previous midquote, I require the midquote to be five seconds older than the trade.

RESULTS – Table 11 reports the estimates of PIN for each stock in the different sample periods. Table 12 shows that moving from the *pre* period to the *post*, the change in the stocks' PIN is not significantly different from zero; comparing, instead, the *pre* with the *post1* and *post2* periods, I find that PIN significantly decreases. The results confirm hypothesis 4 for the *post1* and *post2* periods.

[50] I maximize the likelihood function numerically by using the Nelder-Mead method; the computation is performed through a Matlab routine. The maximization converges for all the stocks in all the four sub-periods. Moreover, I compute the hessian of the parameters of the model by using the Newton-Rhapson-Simpson method and I derive the

4. Conclusions

The introduction of STAR in the Italian equity market represents an ideal natural experiment to study the effect of the activity of specialists with information disclosure obligations. Specialists have obligations in terms of liquidity and disclosure of information; however, liquidity requirements are ineffective and I am able to focus on the role of specialists as information providers. The main finding is that, after firms enter into STAR, spreads and volatility decrease relatively to a matched sample of control stocks. The results can be explained by a decrease in adverse selection costs following the introduction of the specialists. Accordingly, after the entrance in STAR, I find that information asymmetries, measured by the probability of informed trading, decrease. Moreover, I provide evidence that the information disclosed by specialists is perceived as useful for investment decisions.

Unlike specialists in the NYSE, Italian market makers do not manage the order book; their role in supporting trading is analogous to that of specialists operating, for example, in Euronext and in the OMX platform (see, for a review of market making worldwide, Charitou and Panayedes, 2006). The results of the analysis suggest that, in such trading system, imposing disclosure requirements on specialists can be beneficial to market quality for small-medium firms. This way of disseminating information might be preferable when firm-specific incentives for disclosure are not effective.

Recent empirical works consider other European exchanges and generally document that specialists with only liquidity obligations improve market quality; I contribute to this stream of research in that I study the effect of an additional role played by specialists. Furthermore, this work adds to the literature on the economic consequences of disclosure by examining a new form of mandatory change in information disclosure rules.

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standard errors. According to the corresponding *z*-tests, the estimates of the parameters are significantly different from zero at the 10% level.

Table 1. Specialists' liquidity obligations

This table presents the obligations of the specialists. Trading volume is expressed in euro. The spread is the quoted spread as a percentage of the midpoint. The mean daily trading volume refers to the previous semester of trading.

Mean daily trading volume		*Specialists' obligations*		
From	To	Min. daily trading volume	Min. order size	Max spread
0	50,000	15,000	1,000	4.5%
50,001	100,000	25,000	2,500	4.0%
100,001	200,000	50,000	2,500	3.5%
200,001	500,000	75,000	2,500	3.0%
500,001	5,000,000	100,000	2,500	2.5%
5,000,001	10,000,000	400,000	5,000	1.5%
>10,000,000		1,000,000	10,000	1.0%

Table 2: Sample and control stocks

This table presents the stocks in the sample and the corresponding control stocks. The sample contains all the stocks that entered into STAR from November 2000 to February 2006. I excluded four stocks (Centrale del latte Torino, Cementir,Digital Bros and IT Way) because I did not receive compelte data from BIt. The table also reports the maximum spread required (as a percentage of the midquote) for market makers at the entrance of the stocks in STAR and the average spread recorded in the Pre period.

	STAR stocks	*Date of entry in STAR*	*Date of exit from STAR*	*Maximum spread required*	*Average spread in the pre-period*	*Control stocks*
1	Banca Finnat	01/04/2001		0.03	0.0210	Banca Profilo
2	BPEL	01/04/2001		0.045	0.0095	Mediacontech
3	Brembo	01/04/2001		0.04	0.0087	Aeroporto di Firenze
4	Centrale del latte Torino	01/04/2001		-	-	-
5	CSP International	01/04/2001	06/06/2005	0.045	0.0113	Poligrafici Editoriale
6	Ducati	01/04/2001		0.025	0.0050	Monrif
7	ERG	01/04/2001	19/12/2005	0.025	0.0054	SNIA
8	Interpump	01/04/2001		0.035	0.0070	Acegas
9	Irce	01/04/2001		0.045	0.0207	Danieli
10	La Doria	01/04/2001		0.045	0.0116	Basicnet
11	Manuli Rubber Industries	01/04/2001	29/01/2004	0.04	0.0104	Pininfarina
12	Mariella Burani	01/04/2001		0.04	0.0090	ACSM
13	Mirato	01/04/2001		0.045	0.0084	Caltagirone Editore
14	Navigazione Montanari	01/04/2001		0.03	0.0118	Schiapparelli
15	Reno De Medici	01/04/2001		0.035	0.0091	Ergo Previdenza
16	Sabaf	01/04/2001		0.045	0.0068	Permasteelisa
17	Saes Getters	01/04/2001		0.045	0.0150	Data Service
18	Targetti Sankey	01/04/2001		0.04	0.0176	FMR ART 'E'
19	Banca Pop. Intra	01/07/2001		0.045	0.0054	SNAI
20	Cremonini	01/07/2001		0.03	0.0070	Beghelli
21	IMA	01/07/2001		0.045	0.0159	Olidata
22	Jolly Hotels	01/07/2001	03/08/2007	0.045	0.0094	Ricchetti
23	Meliorbanca	01/07/2001		0.035	0.0059	Class Editori
24	Richard Ginori	01/07/2001		0.04	0.0153	Bastogi
25	Aedes	24/09/2001		0.045	0.0084	IPI
26	Amga	24/09/2001	01/11/2006	0.035	0.0078	Eutelia
27	Cembre	24/09/2001		0.045	0.0332	Filatura di Pollone
28	Cementir	24/09/2001	19/03/2007	-	-	-
29	Emak	24/09/2001		0.045	0.0127	Grandi Viaggi
30	Stefanel	24/09/2001		0.045	0.0129	Trevi
31	Vittoria Assicurazioni	26/11/2001		0.045	0.0285	Ciccolella
32	Gefran	27/05/2002		0.045	0.0107	Finarte
33	Sogefi	15/01/2004		0.035	0.0063	Ratti
34	Actelios	20/09/2004		0.045	0.0107	Zucchi
35	Banca Ifis	29/11/2004		0.045	0.0127	Gabetti
36	Acotel Group	19/09/2005		0.045	0.0065	Maffei
37	BB Biotech	19/09/2005		0.045	0.0018	De Longhi
38	Buongiorno	19/09/2005		0.025	0.0030	IMMSI
39	Cad It	19/09/2005		0.045	0.0064	INTEK
40	Cairo Communication	19/09/2005		0.045	0.0038	Viaggi Ventaglio
41	CDC	19/09/2005		0.045	0.0049	Gewiss
42	DADA	19/09/2005		0.04	0.0036	Linificio
43	Datalogic	19/09/2005		0.04	0.0043	Acque potabili
44	Dea Capital	19/09/2005		0.025	0.0032	Premafin
45	Digital Bros	19/09/2005		-	-	-
46	Dmail Group	19/09/2005		0.045	0.0050	AS Roma
47	El.En.	19/09/2005		0.045	0.0060	Caltagiorne
48	Engineering	19/09/2005		0.045	0.0064	SOL

49	Esprinet	19/09/2005	0.03	0.0035	Marcolin
50	Fidia	19/09/2005	0.045	0.0083	CAM-FIN
51	I.Net	19/09/2005	0.04	0.0048	Kaitech
52	IT Way	19/09/2005	-	-	-
53	Mondo TV	19/09/2005	0.045	0.0056	Exprivia
54	Poligrafica S. Faustino	19/09/2005	0.045	0.0043	KME
55	Prima Industrie	19/09/2005	0.045	0.0068	Mittel
56	Reply	19/09/2005	0.045	0.0061	Enertad
57	TAS	19/09/2005	0.045	0.0069	Mediterranea Acque
58	TXT	19/09/2005	0.045	0.0053	Sadi Servizi
59	Fullsix	30/11/2005	0.035	0.0058	Brioschi

Table 3: Spread – descriptive statistics
This table reports the average quoted spread (as a percentage of the midquote) over the four periods considered. The table presents results for STAR stocks and the corresponding control sample.

STAR	*pre*	*post*	*post1*	*post2*	*Control*	*pre*	*post*	*post1*	*post2*
Banca Finnat	0.0210	0.0121	0.0155	0.0094	Banca Profilo	0.0070	0.0064	0.0089	0.0067
BPEL	0.0095	0.0085	0.0064	0.0031	Mediacontech	0.0059	0.0096	0.0079	0.0100
Brembo	0.0087	0.0096	0.0070	0.0031	Aeroporto di Firenze	0.0101	0.0100	0.0089	0.0053
CSP International	0.0113	0.0144	0.0111	0.0139	Poligrafici Editoriale	0.0083	0.0093	0.0122	0.0111
Ducati	0.0050	0.0051	0.0058	0.0033	Monrif	0.0113	0.0091	0.0145	0.0103
ERG	0.0054	0.0042	0.0039	0.0034	SNIA	0.0039	0.0034	0.0038	0.0044
Interpump	0.0070	0.0057	0.0061	0.0038	Acegas	0.0062	0.0062	0.0083	0.0045
Irce	0.0207	0.0107	0.0166	0.0112	Danieli	0.0081	0.0118	0.0163	0.0123
La Doria	0.0116	0.0142	0.0192	0.0183	Basicnet	0.0121	0.0165	0.0105	0.0121
Manuli Rubber Industries	0.0104	0.0098	0.0119	0.0044	Pininfarina	0.0104	0.0105	0.0202	0.0124
Mariella Burani	0.0090	0.0069	0.0089	0.0051	ACSM	0.0092	0.0094	0.0148	0.0093
Mirato	0.0084	0.0081	0.0092	0.0058	Caltagirone Editore	0.0057	0.0047	0.0053	0.0042
Navigazione Montanari	0.0118	0.0084	0.0105	0.0059	Schiapparelli	0.0117	0.0131	0.0166	0.0086
Reno De Medici	0.0091	0.0100	0.0094	0.0061	Ergo Previdenza	0.0097	0.0120	0.0101	0.0057
Sabaf	0.0068	0.0068	0.0050	0.0051	Permasteelisa	0.0101	0.0056	0.0043	0.0022
Saes Getters	0.0150	0.0114	0.0145	0.0135	Data Service	0.0057	0.0071	0.0095	0.0056
Targetti Sankey	0.0176	0.0160	0.0153	0.0085	FMR ART 'E'	0.0082	0.0099	0.0081	0.0052
Banca Pop. Intra	0.0054	0.0105	0.0046	0.0023	SNAI	0.0038	0.0042	0.0090	0.0060
Cremonini	0.0070	0.0089	0.0063	0.0043	Beghelli	0.0094	0.0174	0.0162	0.0100
IMA	0.0159	0.0135	0.0077	0.0050	Olidata	0.0108	0.0169	0.0246	0.0126
Jolly Hotels	0.0094	0.0202	0.0178	0.0111	Ricchetti	0.0109	0.0194	0.0152	0.0085
Meliorbanca	0.0059	0.0110	0.0103	0.0051	Class Editori	0.0035	0.0052	0.0061	0.0056
Richard Ginori	0.0153	0.0149	0.0180	0.0090	Bastogi	0.0077	0.0127	0.0154	0.0120
Aedes	0.0084	0.0097	0.0060	0.0052	IPI	0.0093	0.0120	0.0077	0.0091
Amga	0.0078	0.0038	0.0062	0.0032	Eutelia	0.0048	0.0053	0.0077	0.0067
Cembre	0.0332	0.0166	0.0166	0.0134	Filatura di Pollone	0.0262	0.0232	0.0277	0.0165
Emak	0.0127	0.0142	0.0088	0.0077	Grandi Viaggi	0.0246	0.0180	0.0149	0.0133
Stefanel	0.0129	0.0125	0.0167	0.0085	Trevi	0.0115	0.0136	0.0124	0.0074
Vittoria Assicurazioni	0.0285	0.0120	0.0171	0.0069	Ciccolella	0.0666	0.0392	0.0584	0.0480
Gefran	0.0107	0.0156	0.0089	0.0089	Finarte	0.0168	0.0273	0.0225	0.0401
Sogefi	0.0063	0.0052	0.0032		Ratti	0.0187	0.0262	0.0177	
Actelios	0.0107	0.0051	0.0037		Zucchi	0.0173	0.0130	0.0166	
Banca Ifis	0.0127	0.0078			Gabetti	0.0098	0.0081		
Acotel Group	0.0065	0.0077			Maffei	0.0059	0.0078		
BB Biotech	0.0018	0.0019			De Longhi	0.0034	0.0060		
Buongiorno	0.0030	0.0029			IMMSI	0.0030	0.0034		
Cad It	0.0064	0.0068			INTEK	0.0112	0.0109		
Cairo Communication	0.0038	0.0032			Viaggi Ventaglio	0.0071	0.0079		
CDC	0.0049	0.0046			Gewiss	0.0046	0.0054		
DADA	0.0036	0.0042			Linificio	0.0080	0.0078		
Datalogic	0.0043	0.0041			Acque potabili	0.0191	0.0250		
Dea Capital	0.0032	0.0026			Premafin	0.0038	0.0036		
Dmail Group	0.0050	0.0064			AS Roma	0.0096	0.0098		
El.En.	0.0060	0.0048			Caltagiorne	0.0068	0.0070		
Engineering	0.0064	0.0058			SOL	0.0073	0.0069		
Esprinet	0.0035	0.0030			Marcolin	0.0065	0.0092		
Fidia	0.0083	0.0085			CAM-FIN	0.0043	0.0035		
I.Net	0.0048	0.0054			Kaitech	0.0047	0.0054		
Mondo TV	0.0056	0.0061			Exprivia	0.0043	0.0055		
Poligrafica S. Faustino	0.0043	0.0053			KME	0.0073	0.0090		
Prima Industrie	0.0068	0.0065			Mittel	0.0066	0.0067		

Reply	0.0061	0.0052			Enertad	0.0035	0.0043		
TAS	0.0069	0.0074			Mediterranea Acque	0.0157	0.0204		
TXT	0.0053	0.0056			Sadi Servizi	0.0151	0.0119		
Fullsix	0.0058	0.0042			Brioschi	0.0055	0.0043		
Average STAR	0.0092	0.0083	0.0103	0.0071	*Average Control*	0.0102	0.0109	0.0141	0.0109
St. dev. STAR	0.0060	0.0042	0.0050	0.0039	*St. dev. Control*	0.0093	0.0071	0.0100	0.0097

Table 4: Time-weighted spread – descriptive statistics
This table reports the average time-weighted quoted spread (as a percentage of the midquote) over the four periods considered. The table presents results for STAR stocks and the corresponding control sample.

STAR	*pre*	*post*	*post1*	*post2*	*Control*	*pre*	*post*	*post1*	*post2*
Banca Finnat	0.0201	0.0120	0.0154	0.0092	Banca Profilo	0.0064	0.0060	0.0080	0.0060
BPEL	0.0090	0.0076	0.0059	0.0029	Mediacontech	0.0056	0.0092	0.0073	0.0095
Brembo	0.0087	0.0092	0.0065	0.0029	Aeroporto di Firenze	0.0093	0.0092	0.0083	0.0046
CSP International	0.0104	0.0138	0.0108	0.0135	Poligrafici Editoriale	0.0079	0.0088	0.0115	0.0102
Ducati	0.0048	0.0049	0.0055	0.0032	Monrif	0.0103	0.0083	0.0136	0.0097
ERG	0.0051	0.0040	0.0037	0.0033	SNIA	0.0038	0.0033	0.0037	0.0043
Interpump	0.0066	0.0054	0.0058	0.0036	Acegas	0.0061	0.0057	0.0076	0.0043
Irce	0.0197	0.0100	0.0159	0.0108	Danieli	0.0078	0.0114	0.0140	0.0116
La Doria	0.0116	0.0137	0.0183	0.0181	Basicnet	0.0112	0.0158	0.0099	0.0115
Manuli Rubber Industries	0.0100	0.0091	0.0117	0.0042	Pininfarina	0.0087	0.0104	0.0187	0.0119
Mariella Burani	0.0087	0.0065	0.0085	0.0048	ACSM	0.0087	0.0086	0.0138	0.0083
Mirato	0.0081	0.0080	0.0089	0.0056	Caltagirone Editore	0.0055	0.0046	0.0049	0.0040
Navigazione Montanari	0.0107	0.0081	0.0102	0.0059	Schiapparelli	0.0109	0.0125	0.0156	0.0081
Reno De Medici	0.0083	0.0091	0.0090	0.0057	Ergo Previdenza	0.0091	0.0111	0.0095	0.0054
Sabaf	0.0064	0.0064	0.0045	0.0051	Permasteelisa	0.0094	0.0053	0.0040	0.0020
Saes Getters	0.0141	0.0106	0.0139	0.0131	Data Service	0.0056	0.0067	0.0090	0.0053
Targetti Sankey	0.0165	0.0154	0.0155	0.0084	FMR ART 'E'	0.0080	0.0094	0.0079	0.0051
Banca Pop. Intra	0.0054	0.0096	0.0042	0.0021	SNAI	0.0036	0.0041	0.0084	0.0056
Cremonini	0.0065	0.0083	0.0060	0.0043	Beghelli	0.0089	0.0166	0.0148	0.0092
IMA	0.0139	0.0132	0.0080	0.0050	Olidata	0.0104	0.0154	0.0219	0.0112
Jolly Hotels	0.0090	0.0196	0.0168	0.0104	Ricchetti	0.0099	0.0181	0.0134	0.0079
Meliorbanca	0.0055	0.0106	0.0100	0.0051	Class Editori	0.0032	0.0049	0.0058	0.0053
Richard Ginori	0.0150	0.0139	0.0173	0.0087	Bastogi	0.0072	0.0117	0.0149	0.0112
Aedes	0.0080	0.0095	0.0060	0.0050	IPI	0.0092	0.0113	0.0073	0.0089
Amga	0.0072	0.0035	0.0059	0.0030	Eutelia	0.0043	0.0048	0.0071	0.0064
Cembre	0.0332	0.0158	0.0163	0.0128	Filatura di Pollone	0.0261	0.0222	0.0268	0.0155
Emak	0.0123	0.0134	0.0087	0.0074	Grandi Viaggi	0.0245	0.0170	0.0136	0.0121
Stefanel	0.0135	0.0122	0.0172	0.0080	Trevi	0.0110	0.0125	0.0113	0.0069
Vittoria Assicurazioni	0.0258	0.0121	0.0167	0.0066	Ciccolella	0.0641	0.0376	0.0565	0.0549
Gefran	0.0096	0.0152	0.0086	0.0087	Finarte	0.0106	0.0246	0.0211	0.0388
Sogefi	0.0061	0.0050	0.0031		Ratti	0.0176	0.0248	0.0164	
Actelios	0.0098	0.0049	0.0035		Zucchi	0.0168	0.0127	0.0157	
Banca Ifis	0.0115	0.0076			Gabetti	0.0089	0.0071		
Acotel Group	0.0060	0.0073			Maffei	0.0055	0.0072		
BB Biotech	0.0018	0.0019			De Longhi	0.0032	0.0056		
Buongiorno	0.0028	0.0027			IMMSI	0.0028	0.0033		
Cad It	0.0061	0.0065			INTEK	0.0106	0.0100		
Cairo Communication	0.0036	0.0030			Viaggi Ventaglio	0.0068	0.0073		
CDC	0.0047	0.0046			Gewiss	0.0043	0.0050		
DADA	0.0034	0.0039			Linificio	0.0074	0.0070		
Datalogic	0.0041	0.0039			Acque potabili	0.0186	0.0270		
Dea Capital	0.0031	0.0025			Premafin	0.0036	0.0032		
Dmail Group	0.0048	0.0061			AS Roma	0.0089	0.0092		
El.En.	0.0054	0.0045			Caltagiorne	0.0064	0.0067		
Engineering	0.0060	0.0056			SOL	0.0066	0.0063		
Esprinet	0.0033	0.0029			Marcolin	0.0059	0.0084		
Fidia	0.0080	0.0082			CAM-FIN	0.0040	0.0033		
I.Net	0.0045	0.0052			Kaitech	0.0045	0.0052		
Mondo TV	0.0052	0.0057			Exprivia	0.0042	0.0051		
Poligrafica S. Faustino	0.0040	0.0051			KME	0.0071	0.0083		
Prima Industrie	0.0064	0.0062			Mittel	0.0061	0.0064		

Reply	0.0058	0.0051			Enertad	0.0033	0.0041		
TAS	0.0068	0.0070			Mediterranea Acque	0.0141	0.0184		
TXT	0.0050	0.0054			Sadi Servizi	0.0143	0.0092		
Fullsix	0.0055	0.0040			Brioschi	0.0053	0.0041		
Average STAR	0.0087	0.0079	0.0099	0.0069	*Average Control*	0.0095	0.0102	0.0132	0.0105
St. dev. STAR	0.0058	0.0041	0.0049	0.0039	*St. dev. Control*	0.0089	0.0069	0.0096	0.0106

Table 5: Volatility – descriptive statistics
This table reports the average realized volatility, defined as in Section 4, over the four periods considered. The table presents results for STAR stocks and the corresponding control sample.

STAR	*pre*	*post*	*post1*	*post2*	*Control*	*pre*	*post*	*post1*	*post2*
Banca Finnat	0.0453	0.0324	0.0460	0.0436	Banca Profilo	0.0536	0.0386	0.0563	0.0416
BPEL	0.0321	0.0385	0.0429	0.0236	Mediacontech	0.0345	0.0433	0.0354	0.0346
Brembo	0.0316	0.0335	0.0379	0.0207	Aeroporto di Firenze	0.0418	0.0436	0.0373	0.0391
CSP International	0.0335	0.0332	0.0358	0.0430	Poligrafici Editoriale	0.0564	0.0446	0.0514	0.0460
Ducati	0.0291	0.0322	0.0410	0.0259	Monrif	0.0500	0.0393	0.0567	0.0452
ERG	0.0272	0.0263	0.0343	0.0255	SNIA	0.0248	0.0237	0.0226	0.0335
Interpump	0.0293	0.0258	0.0361	0.0254	Acegas	0.0295	0.0389	0.0414	0.0228
Irce	0.0415	0.0373	0.0467	0.0311	Danieli	0.0273	0.0253	0.0568	0.0389
La Doria	0.0248	0.0250	0.0337	0.0319	Basicnet	0.0473	0.0512	0.0874	0.0389
Manuli Rubber Industries	0.0337	0.0344	0.0447	0.0183	Pininfarina	0.0396	0.0364	0.0685	0.0477
Mariella Burani	0.0304	0.0284	0.0254	0.0191	ACSM	0.0406	0.0372	0.0545	0.0302
Mirato	0.0221	0.0302	0.0411	0.0161	Caltagirone Editore	0.0291	0.0274	0.0360	0.0267
Navigazione Montanari	0.0655	0.0301	0.0352	0.0239	Schiapparelli	0.0390	0.0323	0.0617	0.0603
Reno De Medici	0.0365	0.0384	0.0459	0.0384	Ergo Previdenza	0.0345	0.0459	0.0612	0.0393
Sabaf	0.0210	0.0311	0.0249	0.0191	Permasteelisa	0.0357	0.0279	0.0380	0.0210
Saes Getters	0.0440	0.0445	0.0572	0.0360	Data Service	0.0487	0.0416	0.0383	0.0288
Targetti Sankey	0.0362	0.0459	0.0337	0.0234	FMR ART 'E'	0.0413	0.0427	0.0334	0.0223
Banca Pop. Intra	0.0236	0.0498	0.0255	0.0180	SNAI	0.0427	0.0578	0.0776	0.0543
Cremonini	0.0355	0.0432	0.0327	0.0461	Beghelli	0.0348	0.0577	0.0873	0.0573
IMA	0.0308	0.0278	0.0508	0.0236	Olidata	0.0400	0.0719	0.0958	0.0492
Jolly Hotels	0.0253	0.0534	0.0531	0.0359	Ricchetti	0.0335	0.0516	0.0536	0.0369
Meliorbanca	0.0312	0.0397	0.0466	0.0177	Class Editori	0.0313	0.0477	0.0604	0.0471
Richard Ginori	0.0265	0.0488	0.0391	0.0332	Bastogi	0.0370	0.0615	0.0922	0.0577
Aedes	0.0409	0.0331	0.0229	0.0208	IPI	0.0232	0.0369	0.0257	0.0158
Amga	0.0413	0.0216	0.0323	0.0186	Eutelia	0.0527	0.0459	0.0524	0.0341
Cembre	0.0410	0.0189	0.0395	0.0224	Filatura di Pollone	0.0383	0.0227	0.0530	0.0423
Emak	0.0371	0.0302	0.0286	0.0206	Grandi Viaggi	0.0391	0.0687	0.0880	0.0518
Stefanel	0.0428	0.0404	0.0556	0.0381	Trevi	0.0422	0.0473	0.0574	0.0379
Vittoria Assicurazioni	0.0834	0.0286	0.0329	0.0249	Ciccolella	0.1087	0.0627	0.0540	0.0263
Gefran	0.0497	0.0486	0.0202	0.0159	Finarte	0.0507	0.0732	0.0561	0.0753
Sogefi	0.0366	0.0336	0.0163		Ratti	0.0620	0.0713	0.0600	
Actelios	0.0392	0.0167	0.0238		Zucchi	0.0474	0.0229	0.0386	
Banca Ifis	0.0331	0.0213			Gabetti	0.0512	0.0375		
Acotel Group	0.0256	0.0212			Maffei	0.0230	0.0213		
BB Biotech	0.0053	0.0056			De Longhi	0.0237	0.0284		
Buongiorno	0.0213	0.0184			IMMSI	0.0193	0.0232		
Cad It	0.0223	0.0215			INTEK	0.0279	0.0252		
Cairo Communication	0.0154	0.0145			Viaggi Ventaglio	0.0335	0.0327		
CDC	0.0202	0.0177			Gewiss	0.0205	0.0213		
DADA	0.0222	0.0236			Linificio	0.0314	0.0289		
Datalogic	0.0163	0.0203			Acque potabili	0.0147	0.0012		
Dea Capital	0.0211	0.0171			Premafin	0.0241	0.0226		
Dmail Group	0.0210	0.0180			AS Roma	0.0409	0.0335		
El.En.	0.0382	0.0212			Caltagiorne	0.0256	0.0216		
Engineering	0.0224	0.0189			SOL	0.0264	0.0234		
Esprinet	0.0227	0.0173			Marcolin	0.0357	0.0395		
Fidia	0.0256	0.0292			CAM-FIN	0.0242	0.0189		
I.Net	0.0193	0.0165			Kaitech	0.0217	0.0271		
Mondo TV	0.0197	0.0220			Exprivia	0.0203	0.0197		
Poligrafica S. Faustino	0.0232	0.0207			KME	0.0323	0.0375		
Prima Industrie	0.0219	0.0252			Mittel	0.0261	0.0192		

Reply	0.0224	0.0223			Enertad	0.0199	0.0227		
TAS	0.0250	0.0214			Mediterranea Acque	0.0349	0.0389		
TXT	0.0203	0.0182			Sadi Servizi	0.0479	0.0510		
Fullsix	0.0271	0.0276			Brioschi	0.0284	0.0267		
Average STAR	0.0306	0.0284	0.0369	0.0267	*Average Control*	0.0366	0.0375	0.0559	0.0401
St. Dev. STAR	0.0124	0.0104	0.0104	0.0088	*St. Dev. Control*	0.0147	0.0156	0.0193	0.0133

Table 6: Trading volume – descriptive statistics
This table reports the average daily trading volume (in euro), over the four periods considered. The table presents results for STAR stocks and the corresponding control sample.

STAR	*pre*	*post*	*post1*	*post2*	*Control*	*pre*	*post*	*post1*	*post2*
Banca Finnat	55,197	21,041	19,175	133,809	Banca Profilo	431,863	237,814	109,200	103,256
BPEL	80,981	61,900	81,476	971,263	Mediacontech	328,841	42,380	90,678	28,807
Brembo	177,408	82,188	200,908	454,254	Aeroporto Firenze	115,432	58,889	42,047	604,580
CSP International	57,266	24,848	43,044	20,398	Poligrafici Editoriale	163,467	61,317	84,926	58,351
Ducati	607,645	230,227	182,629	264,400	Monrif	80,119	26,457	26,244	27,009
ERG	623,339	870,540	609,448	491,349	SNIA	945,244	1,192,861	765,877	960,585
Interpump	306,808	274,260	306,305	569,361	Acegas	111,109	265,826	70,155	156,663
Irce	22,474	50,626	13,108	10,435	Danieli	58,871	28,654	39,892	34,129
La Doria	29,428	17,010	8,388	9,454	Basicnet	33,187	16,672	960,033	23,831
Manuli Rubber Industries	37,610	34,905	21,158	145,364	Pininfarina	352,452	90,113	72,333	71,308
Mariella Burani	242,493	216,440	96,095	251,365	ACSM	98,685	30,652	18,861	20,699
Mirato	73,065	44,284	92,401	34,951	Caltagirone Editore	537,046	152,401	171,568	221,062
Navigazione Montanari	284,281	98,861	40,976	80,519	Schiapparelli	52,410	21,200	18,768	298,484
Reno De Medici	133,619	54,454	83,157	191,839	Ergo Previdenza	497,629	162,963	185,079	363,919
Sabaf	152,726	158,051	209,126	72,482	Permasteelisa	502,021	438,192	915,244	2,032,844
Saes Getters	285,257	175,322	46,558	22,264	Data Service	359,024	102,370	149,164	271,852
Targetti Sankey	74,118	23,407	11,933	22,014	FMR ART 'E'	122,965	27,084	64,807	54,470
Banca Pop. Intra	148,495	150,841	167,372	694,487	SNAI	1,250,580	1,775,783	285,447	684,545
Cremonini	174,066	79,223	74,343	176,068	Beghelli	44,541	33,462	27,990	168,424
IMA	149,754	100,624	141,331	138,102	Olidata	44,584	68,980	22,575	43,335
Jolly Hotels	91,460	32,217	7,701	30,776	Ricchetti	51,632	31,414	14,834	56,505
Meliorbanca	267,034	137,536	68,087	147,169	Class Editori	1,407,537	911,751	503,964	403,732
Richard Ginori	69,262	60,042	12,270	39,949	Bastogi	102,772	67,929	33,042	99,956
Aedes	68,610	47,741	55,241	161,875	IPI	41,986	70,358	135,514	16,930
Amga	87,665	261,185	117,568	179,556	Eutelia	280,981	425,815	251,079	78,897
Cembre	8,209	5,889	11,126	15,791	Filatura di Pollone	6,299	6,778	8,230	37,948
Emak	40,274	19,519	25,248	35,974	Grandi Viaggi	7,393	39,915	59,220	45,851
Stefanel	14,049	25,068	14,725	145,737	Trevi	108,055	42,818	31,979	115,155
Vittoria Assicurazioni	16,966	38,219	17,773	74,896	Ciccolella	9,924	3,682	1,599	-
Gefran	49,691	16,919	17,503	23,728	Finarte	41,623	25,404	10,208	10,747
Sogefi	288,029	250,753	450,630		Ratti	53,382	7,389	77,533	
Actelios	33,947	48,736	792,776		Zucchi	40,494	26,103	42,342	
Banca Ifis	34,808	94,001			Gabetti	356,341	229,431		
Acotel Group	65,422	41,424			Maffei	149,636	57,552		
BB Biotech	377,511	405,368			De Longhi	497,537	172,482		
Buongiorno	811,707	649,714			IMMSI	772,420	1,577,670		
Cad It	115,666	63,315			INTEK	119,585	66,374		
Cairo Communication	250,037	393,996			Viaggi Ventaglio	133,635	125,571		
CDC	102,948	92,735			Gewiss	187,304	268,634		
DADA	548,219	362,289			Linificio	111,941	115,254		
Datalogic	160,518	551,563			Acque potabili	12,029			
Dea Capital	2,281,893	672,782			Premafin	480,324	1,461,752		
Dmail Group	126,178	115,304			AS Roma	78,935	56,243		
El.En.	315,982	261,087			Caltagiorne	112,953	89,131		
Engineering	231,607	178,757			SOL	186,289	118,615		
Esprinet	707,940	1,452,468			Marcolin	327,270	149,803		
Fidia	70,239	93,157			CAM-FIN	618,905	681,736		
I.Net	97,597	68,143			Kaitech	193,005	236,087		
Mondo TV	149,848	111,267			Exprivia	229,250	96,590		
Poligrafica S. Faustino	338,375	213,322			KME	284,015	197,879		
Prima Industrie	102,802	241,642			Mittel	161,487	123,327		

Reply	135,247	121,443			Enertad	563,764	450,262		
TAS	163,071	48,550			Medit. Acque	16,087	32,679		
TXT	196,579	105,240			Sadi Servizi	75,291	323,647		
Fullsix	308,326	1,257,481			Brioschi	345,885	345,234		
Average STAR	226,250	205,599	126,237	186,988	*Average Control*	259,928	249,433	165,326	244,616
St. Dev. STAR	334,856	289,029	181,337	229,980	*St. Dev. Control*	296,693	401,124	256,254	413,114

Table 7: Univariate tests

This table compares the difference in the measures of market quality (quoted spread in Panel A, time-weighted quoted spread in Panle B, volatility in Panel 3, and trading volume in Panel D) examined between the periods after the introduction of the specialists and the *pre* period. The average difference for STAR (column STAR) and control (column Control) stocks are reported; in addtion, the difference in differences (column STAR-Control), defined as *DID* in Section 4, is presented. A t-test and a Wilcoxon signed-rank test for the null hypothesis that the average or the meadian of *DID* is equal to zero are presented. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel 1: Spread

	STAR	*Control*	*STAR-Control*	*t-test*	*Wilcoxon*
post-pre	-0.0009	0.0007	-0.0016	-2.6907***	-2.958***
post1-pre	-0.0016	0.0021	-0.0036	-3.2737***	-3.104***
post2-pre	-0.0049	-0.0008	-0.0041	-3.3436***	-3.096***

Panel 2: Time-weighted spread

	STAR	*Control*	*STAR-Control*	*t-test*	*Wilcoxon*
post-pre	-0.0008	0.0007	-0.0015	-2.3833***	-2.765***
post1-pre	-0.0013	0.0019	-0.0032	-3.0686***	-2.805***
post2-pre	-0.0046	-0.0004	-0.0042	-3.2089***	-3.137***

Panel 3: Volatility

	STAR	*Control*	*STAR-Control*	*t-test*	*Wilcoxon*
post-pre	-0.0022	0.0009	-0.0031	-1.9967*	-1.676*
post1-pre	0.0004	0.0135	-0.0131	-3.4537***	-2.805***
post2-pre	-0.0097	-0.0015	-0.0082	-2.2512***	-2.026**

Panel 4: Trading volume

	STAR	*Control*	*STAR-Control*	*t-test*	*Wilcoxon*
post-pre	-28,275	-15,086	-13,190	-0.2146	0.9
post1-pre	-22,239	-93,491	71,252	1.1811	1.421
post2-pre	38,705	-37,396	76,101	0.827	0.984

Table 8: Multivariate analysis (1)

This table reports the results of the regression: $y_{i,t} = \beta_0 + \beta_1 Control_i + \beta_2 After_{i,t} + \beta_3 (After_{i,t} * Control_i) + \varepsilon_i$; where the subscript *i* refers to stock *i*, the subscript *t* refers to day *t*, *control* is a dummy variable for the control stocks, *after* is a dummy variable for the period after the introduction of STAR; *y* is either the quoted spread (Panel A), or the time-weighted quoted spread (Panel B), or volatility (Panel C), or trading volume (Panel D). The model is estimated using data from the periods *pre* and *post* (column *pre vs. post*), or from the periods *pre* and *post1* (columns *pre vs. post1*) or from the periods *pre* and *post2* (column *pre vs. post2*). *T*-tests are reported in brackets. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Spread

	pre vs. post	*pre vs. post1*	*pre vs. post2*
Constant	0.0090***	0.0118***	0.0114***
	(61.44)	(48.03)	(63.51)
After	-0.0007***	-0.0015***	-0.0043***
	(-3.79)	(-4.58)	(-17.18)
Control	0.0010***	0.0002	-0.0018***
	(4.99)	(0.82)	(-7.06)
(Control)*(After)	0.0014***	0.0034***	0.0042***
	(5.03)	(7.04)	(11.86)
R^2	0.0122	0.0147	0.0394

Panel B: Time-weighted spread

	pre vs. post	*pre vs. post1*	*pre vs. post2*
Constant	0.0085***	0.0111***	0.0108***
	(61.15)	(47.72)	(63.4)
After	-0.0006***	-0.0012***	-0.0040***
	(-3.3)	(-3.81)	(-16.71)
Control	0.0010***	0.0003	-0.0016***
	(5.11)	(1.12)	(-6.97)
(Control)*(After)	0.0011***	0.0025***	0.0038***
	(4.08)	(5.52)	(11.28)
R^2	0.0103	0.0102	0.0373

Panel C: Volatility

	pre vs. post	*pre vs. post1*	*pre vs. post2*
Constant	0.0307***	0.0372***	0.0355***
	(46.66)	(32.41)	(36.51)
After	-0.0021**	-0.0002	-0.0087***
	(-2.35)	(-0.15)	(-6.42)
Control	0.0060***	0.0059***	0.0036***
	(6.43)	(3.63)	(2.65)
(Control)*(After)	0.0034**	0.0128***	0.0101***
	(2.59)	(5.64)	(5.28)
R^2	0.0102	0.0221	0.0172

Panel D: Trading volume

	pre vs. post	*pre vs. post1*	*pre vs. post2*
Constant	232507.4***	152796.2***	156808.3***
	(19.73)	(13.95)	(9.79)
After	-29611.23*	-22525.36	38466.61*
	(-1.78)	(-1.47)	(1.72)
Control	32014.19*	111140.7***	127998.6***
	(1.92)	(7.17)	(5.67)
(Control)*(After)	16651.9	-72267.15***	-71878.71**
	(0.71)	(-3.33)	(-2.28)
R^2	0.0011	0.0109	0.0053

Table 9: Multivariate analysis (2) – model with fixed effects

This table reports the results of the regression: $y_{i,t} = \beta_0 + \beta_1 Control_i + \beta_2 After_{i,t} + \beta_3 (After_{i,t} * Control_i) + \varepsilon_i$; where the subscript *i* refers to stock *i*, the subscript *t* refers to day *t*, *control* is a dummy variable for the control stocks, *after* is a dummy variable for the period after the introduction of STAR; *y* is either the quoted spread (Panel A), or the time-weighted quoted spread (Panel B), or volatility (Panel C), or trading volume (Panel D). The model is estimated using data from the periods *pre* and *post* (column *pre vs. post*), or from the periods *pre* and *post1* (columns *pre vs. post1*) or from the periods *pre* and *post2* (column *pre vs. post2*). Firm-pair fixed effects (for each pair of sample/control stocks) are used. *Z*-tests are reported in brackets.***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Spread

	pre vs. post	*pre vs. post1*	*pre vs. post2*
Constant	0.0090***	0.0116***	0.0113***
	(73.88)	(56.3)	(67.76)
After	-0.0008***	-0.0014***	-0.0043***
	(-4.42)	(-4.98)	(-18.42)
Control	0.0012***	0.0007**	-0.0014***
	(7.2)	(2.28)	(-6.06)
(Control)*(After)	0.0015***	0.0035***	0.0042***
	(6.03)	(8.63)	(12.77)
R^2	0.0121	0.0145	0.0389

Panel B: Time-weighted spread

	pre vs. post	*pre vs. post1*	*pre vs. post2*
Constant	0.0084***	0.0108***	0.0107***
	(73.6)	(55.19)	(67.76)
After	-0.0006***	-0.0011***	-0.0039***
	(-3.79)	(-4.01)	(-17.95)
Control	0.0012***	0.0008***	-0.0013***
	(7.44)	(2.79)	(-5.94)
(Control)*(After)	0.0011***	0.0027***	0.0038***
	(4.68)	(6.96)	(12.16)
R^2	0.0103	0.01	0.0367

Panel C: Volatility

	pre vs. post	*pre vs. post1*	*pre vs. post2*
Constant	0.0307***	0.0372***	0.0356***
	(48.21)	(32.55)	(36.59)
After	-0.0022**	-0.0001	-0.0087***
	(-2.52)	(-0.04)	(-6.42)
Control	0.0063***	0.0057***	0.003419**
	(6.97)	(3.52)	(2.46)
(Control)*(After)	0.0033***	0.0132***	0.0103***
	(2.61)	(5.87)	(5.38)
R^2	0.0103	0.022	0.0172

Panel D: Trading volume

	pre vs. post	*pre vs. post1*	*pre vs. post2*
Constant	232945.8***	157420***	161335.5***
	(20.5)	(14.83)	(10.34)
After	-27657.5*	-22891.4	38044.96*
	(-1.73)	(-1.55)	(1.76)
Control	26989.18*	103935.7***	119897***
	(1.67)	(6.88)	(5.42)
(Control)*(After)	22393.03	-73357.8***	-70710.1**
	(0.99)	(-3.5)	(-2.31)
R^2	0.0011	0.0109	0.0053

Table 10: Event study around roadshows

This table reports the mean absolute abnormal returns and abnormal volume in the days around roadshows. Absolute abnormal returns and abnormal volume are defined in Section 5. Day 0 refers to the day of the roadshow. *T*-tests for the null hypothesis that the average absolute abnormal returns or that average abnormal volume are equal to zero are also presented. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Absolute abnormal returns		*Abnormal volume*	
Day	*Average*	*T-test*	*Average*	*T-test*
-20	0.0011	0.0224	0.0345	0.7046
-19	-0.0430	-0.9333	0.0052	0.0942
-18	-0.0659	-1.5480	0.0235	0.4210
-17	-0.0541	-1.3777	0.0446	0.9007
-16	-0.0658*	-1.7231	0.0374	0.8692
-15	0.0238	0.5923	0.0366	0.8185
-14	-0.1202***	-3.3076	-0.0359	-0.7538
-13	0.0107	0.2582	-0.0136	-0.3433
-12	-0.0176	-0.4280	0.0260	0.6477
-11	0.0036	0.0795	0.0590	1.2464
-10	0.0674	1.4439	0.0483	1.2035
-9	0.0371	0.8422	0.0421	0.8912
-8	0.0352	0.8138	0.0844*	1.7245
-7	0.0535	1.2754	0.0839*	1.7506
-6	0.0360	0.8121	0.1145**	2.3574
-5	0.0812*	1.6878	0.0910*	1.8252
-4	0.0183	0.3910	0.1579**	2.5489
-3	0.0895*	1.7197	0.1787***	3.1695
-2	-0.0210	-0.4513	0.1650***	2.9786
-1	0.1358***	2.7007	0.1626***	3.7867
0	0.2530***	4.2209	0.2503***	4.1516
1	0.1865***	3.6262	0.2771***	5.0908
2	0.1952***	3.5723	0.1905***	3.5931
3	0.1089**	2.3817	0.0605	1.5570
4	0.0508	1.0621	0.1485***	2.8341
5	0.0992	1.4592	0.1774***	3.3331
6	0.0754	1.4713	0.1473**	2.4301
7	0.1832***	2.9164	0.1471**	2.4962
8	0.0737	1.3864	0.1921***	2.6827
9	-0.0305	-0.6977	0.0577	1.2731
10	0.0140	0.2836	0.0690	1.5705
11	0.0763	1.5375	0.0605	1.2876
12	0.0712	1.5782	0.1211	1.4843
13	0.0228	0.5209	0.1207	1.4871
14	-0.0109	-0.2567	0.1055	1.6184
15	-0.0676	-1.5907	0.0651	1.5908
16	0.0130	0.2579	0.0708	1.3762
17	0.0294	0.5836	0.0013	0.0297
18	0.0011	0.0217	0.0276	0.6724
19	-0.0268	-0.5984	0.0460	1.0043
20	-0.0547	-1.2052	0.0486	0.9533

Table 11: Probability of informed trading – descriptive statistics
This table reports the estimates of the probability of informed trading (PIN) for each stock for the four sub-periods considered. It also presents the difference between the periods after the introduction in STAR and the *pre* period. PIN was not computed for the stocks with, on average, less than ten buy and ten sell contracts in the period *pre*.

	Average PIN				*Difference in PIN*		
	pre	*post*	*post1*	*post2*	*post-pre*	*post1-pre*	*post2-pre*
BPEL	0.2299	0.1752	0.1200	0.2536	-0.0547	-0.1099	0.0237
Brembo	0.3228	0.3335	0.4487	0.2286	0.0107	0.1259	-0.0942
CSP International	0.2314	0.2305	0.2388	0.1998	-0.0009	-0.0074	-0.0316
Ducati	0.3340	0.1983	0.2079	0.1798	-0.1357	-0.1261	-0.1542
ERG	0.2079	0.1597	0.1898	0.1778	-0.0482	-0.0181	-0.0301
Interpump	0.2573	0.3043	0.1948	0.1698	0.0470	-0.0625	-0.0875
Mariella Burani	0.2737	0.1929	0.2299	0.2241	-0.0808	-0.0438	-0.0496
Mirato	0.2531	0.2997	0.2538	0.2210	0.0466	0.0007	-0.0321
Navigazione Montanari	0.2598	0.3218	0.2179	0.2167	0.0620	-0.0419	-0.0431
Reno De Medici	0.2461	0.1630	0.1809	0.1599	-0.0831	-0.0652	-0.0862
Sabaf	0.2987	0.2466	0.2135	0.2137	-0.0521	-0.0852	-0.0850
Saes Getters	0.3126	0.2892	0.2723	0.3071	-0.0234	-0.0403	-0.0055
Targetti Sankey	0.3493	0.3371	0.2393	0.2864	-0.0122	-0.1100	-0.0629
Banca Pop. Intra	0.2064	0.2383	0.1818	0.1976	0.0319	-0.0246	-0.0088
Cremonini	0.2061	0.2639	0.1550	0.1670	0.0578	-0.0511	-0.0391
IMA	0.4741	0.3811	0.2825	0.3027	-0.0930	-0.1916	-0.1714
Jolly Hotels	0.2380	0.2172	0.2160	0.2883	-0.0208	-0.0220	0.0503
Meliorbanca	0.2621	0.3183	0.2287	0.2385	0.0562	-0.0334	-0.0236
Richard Ginori	0.1903	0.1808	0.1551	0.2741	-0.0095	-0.0352	0.0838
Aedes	0.2182	0.1600	0.1848	0.2273	-0.0582	-0.0334	0.0091
Amga	0.1458	0.2462	0.2121	0.1952	0.1004	0.0663	0.0494
Cementir	0.2781	0.2347	0.2477	0.1742	-0.0434	-0.0304	-0.1039
Gefran	0.1632	0.1836	0.2193	0.1204	0.0204	0.0561	-0.0429
Sogefi	0.1933	0.1905	0.2352		-0.0028	0.0419	
Actelios	0.2681	0.1877	0.2473		-0.0804	-0.0208	
Banca Ifis	0.2316	0.2555			0.0239		
Acotel Group	0.1965	0.2702			0.0737		
BB Biotech	0.1822	0.2070			0.0248		
Buongiorno	0.1610	0.1770			0.0160		
Cad It	0.2439	0.1717			-0.0722		
Cairo Communication	0.2117	0.1657			-0.0460		
CDC	0.2205	0.1737			-0.0468		
DADA	0.2453	0.2521			0.0068		
Datalogic	0.2318	0.1850			-0.0468		
Dea Capital	0.2000	0.1886			-0.0114		
Dmail Group	0.2575	0.2264			-0.0311		
El.En.	0.2397	0.1889			-0.0508		
Engineering	0.2526	0.1784			-0.0742		
Esprinet	0.2214	0.3528			0.1314		
Fidia	0.2749	0.2773			0.0024		
I.Net	0.1949	0.2777			0.0828		
Mondo TV	0.2330	0.2380			0.0050		
Poligrafica S. Faustino	0.4150	0.0718			-0.3432		
Prima Industrie	0.2256	0.3098			0.0842		
Reply	0.2254	0.2096			-0.0158		
TAS	0.1577	0.2791			0.1214		
TXT	0.2467	0.1737			-0.0730		
Fullsix	0.2085	0.3175			0.1090		
Average PIN	0.2437	0.2334	0.2229	0.2184			

Table 12: Variation in the probability of informed trading

This table compares the average difference in the probability of informed trading between the periods after the introduction in STAR and the *pre* period. A paired-sample *t*-test and a Wilcoxon signed-rank test for the null hypothesis that the average or the median difference is equal to zero are presented. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	post-pre	*post1-pre*	*post2-pre*
Average	0.0103	0.0339	0.0407
t-test	0.9087	2.5888***	3.1382***
Wilcoxon	0.708	2.408***	2.677***

Figure 1. Absolute abnormal returns around roadshows

This figure reports the mean absolute abnormal returns, defined as in Section 5, in the days around roadshows. Day 0 corresponds to the disclosure date. The *x*-axis indicates the day, the *y*-axis indicates the mean absolute abnormal returns.

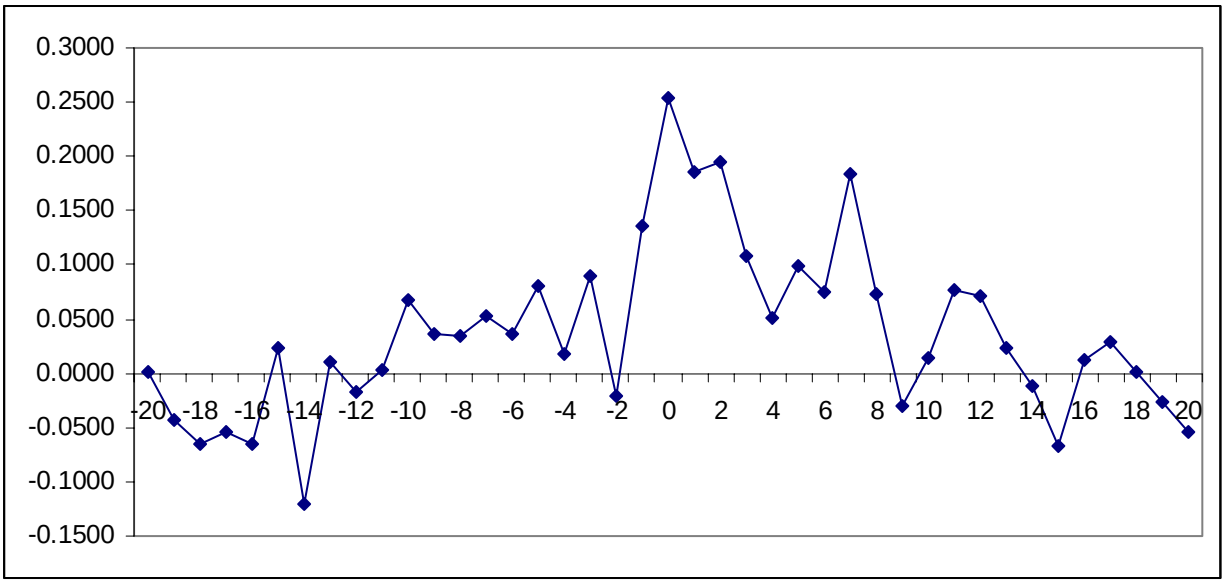
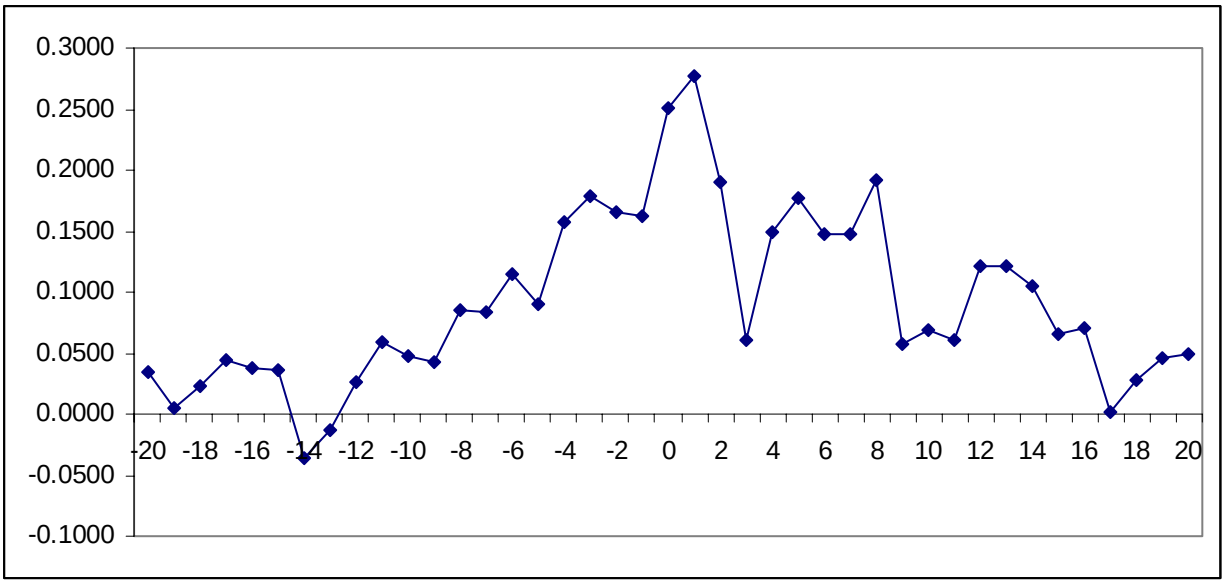


Figure 2. Abnormal volume around roadshows

This figure reports the mean abnormal, defined as in Section 5, in the days around roadshows. Day 0 corresponds to the disclosure date. The *x*-axis indicates the day, the *y*-axis indicates the mean absolute abnormal returns.



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