Price-Volume Relationships in Financial Markets

by

Jesús-Guillermo Llorente-Alvarez

Submitted to the Department of Economics
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A mis padres Alberto y Remedios,
y hermanos Raquel y Alberto.

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Abstract

This dissertation is composed of three papers about the empirical relationships between price and trading volume in the financial markets. The first paper studies the relationship between the price dynamics and trading volume on individual stocks as a consequence of the information transmitted to the market by the trading volume. Trading volume is important because it is correlated with other unobservable variables. This paper studies the relationship between stock trading volume and the autocorrelation of daily stock returns on individual securities. The major finding is that trading volume matters and its importance depends on the size of the stock: the stock return autocorrelation tends to decline with trading volume for large stocks and to increase with trading volume for small stocks. My results support theories which suggest that there are fewer uninformative trades in small stocks relative to large stocks. The results are robust to the consideration of possible non-trading and transactions cost effects.

The second paper investigates the behavior of price and volume around quarterly earning announcements using non-parametric techniques. Grouping stocks by market capitalization, we find evidence of different behavior among them depending on stock size. For large and medium sized stocks, there is arrival of new information to the market before the announcement. Trading volume peaks the event day as a consequence of the revealed information. The direction of the daily change in trading volume is related to the contemporaneous return. The joint density of returns and trading volume is approximately symmetric around zero return and is asymmetric around the mode in the turnover dimension. The joint density on the announcement day has fatter but not longer tails than any other day.

The third paper studies the informational content of trading volume per se and about its identification function in price reversals using different trading strategy schemes. We find evidence about the information impounded in volume and its difference from that of return information. This result is robust to the stock size and to different time horizons. We also find evidence of price reversals for all stocks independently of the trading volume.

Thesis Supervisor: Jiang Wang
Title: Associate Professor

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Jesús-Guillermo Llorente-Alvarez
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Chapter 1

Introduction

Price and trading volume are two important variables to describe financial markets. The finance literature considers trading volume as a variable that reflects the changes in expectations or the heterogeneity of views of individual investors. Volume reflects the activity of investors by summing all the market trades. Price is considered as a variable that reflects changes in expectations of the market. It reflects an aggregation or averaging of investors' beliefs into a single market price. Thus, both variables can react differently to the arrival of new information to the market.

The theoretical literature on asset pricing is extensive. The determination of prices is well understood; empirically there are many papers which successfully test existing models. Contrary to the asset pricing, the theoretical literature on trading volume is more recent and less developed. Until recently, the asset market literature focused solely upon prices with only minor attention devoted to the behavior of trading volume. A theory of volume has to explain not only the level of volume but also the timing of the trades. Thus, a model of trading is not a trivial task.

In a complete market with several agents there is no trading after the initial trading day. Thus, some degree of incompleteness is needed to justify the trading in heterogeneous preference models (i.e. Campbell et al. (1993)). Similarly heterogeneous information models must be augmented to explain trading, either by assuming that agents receive heterogeneous market signals (usually unobservable liquidity shocks) (Wang (1993) and Blume et al. (1994)), or by assuming that agents possess different prior beliefs (Harris and Raviv (1993) and Kandel and Pearson (1993)). One attractive feature of models with market incompleteness or heterogeneous information is their time series implications about the joint behavior of price and volume. The models in these groups are usually divided in two branches: rational expectation asset pricing models and models based on differences of opinion. In the rational expectation models the disagreement (and thus trading) is generated through private information. Differences of opinion models assume that traders receive common information but differ in the way in which they process this information.

Trading in the rational expectations models is not generated by public information. Disagreement and trading is generated through private information. Thus such models usually require three types of agents: informed traders, uninformed traders and noise (or liquidity) traders. There is always some noise that prevents the market from infering why a given trade occurs (portfolio rebalancing, new information, liquidity reasons, speculation motives...). Consequently, agents attempt to infer the information of others from their behavior and from market prices, but there is always some noise that precludes the complete knowledge. Trading in these models is usually driven by exogenous shocks.

The differences of opinion approach focuses upon investor reaction to public news. Trading is motivated by the disagreement among traders over the relationship between an announcement and the response of asset prices to the announcement because they interpret the commonly known data differently. Consequently, these models ignore any learning from prices or any relation to market noise. In addition, investors are not influenced by the behavior or beliefs of others.

There are multiple empirical studies on volume (see Karpoff (1987)). Most of these papers study either the relationship between volume and absolute prices or price variance overtime, or about the volume performance around some public announcement.

Their main results are: *i)* there exists positive correlation between absolute price changes and volume, *ii)* volume is positively autocorrelated, and *iii)* there exist "abnormal" volume on the announcement days. Though these results are interesting and according with received theory, these papers do not test the theoretical predictions of more recent models of price and volume. Thus, there is a need for more empirical study of the relationship between price and volume.

The three chapters that compose this thesis study the empirical relationships between price and volume in financial markets in three different ways. For each chapter existing theoretical work motivates the approach and explains the results. Although, our work should be considered mainly as empirical testing of theory, our work does also yield insights ripe for further theoretical treatment. Though the three chapters are separate entities, considered together, they constitute an interesting work about the relationships between these two variables in three different situations.

The first chapter, titled *Autocorrelation in Returns and Trading Volume on Individual Stocks*, studies the influence of trading volume on the autocorrelation of returns for individual stocks. Trading volume is important for its relationships with unobservable characteristic variables, the degree of investors' heterogeneity of views.

In this chapter we consider two measures of trading volume. One of them related to the whole market that we associate with public information. The other measure is the individual trading in each stock that represents the idiosyncratic unobservable characteristics of each stock. Classifying the stocks by size, we show that trading volume matters in accordance with theory, and that its influence on the autocorrelation of returns depends on the stock market capitalization. The stock return autocorrelation tends to decline with trading volume for large stocks and to increase for small stocks. The results are robust to the consideration of posible alternative or simultaneous explicative variables as well as trading cost and non-trading effects. The consideration of individual stocks and their division by size as well as the study of the robutness of the results to other alternative clasifications are the main novelties of this study in the empirical literature of trading volume. This leads to important conclusions unkown until now.

The second chapter, titled *Price-Volume Behavior Around Announcements: A Non-parametric Approach*, studies the joint relationships between both variables before, after, and on the day of quarterly earning announcements by the individual firms using non-parametric statistical techniques.

There is a considerable empirical literature that studies the "abnormal" behavior of both variables on the announcement dates (usually earning, dividend or split announcements). In order to define what is "abnormal", these studies must postulate a priori what is considered as normal. This allows testing the null hypothesis of "abnormal" behavior on this day. Though in most of the cases they accept the null hypothesis their conclusions are not immune from criticism of their methods. None of them studies the behavior the days before and after the event date.

The specification free characteristic of the non-parametric methods allows us to describe patterns of behavior during these days with out imposing a priori restrictive functional forms. With this methodology we are able to study the density functions of price and volume (both joint and conditional densities) as well as conditional expectations and variances. Though we are not able to test any null hypothesis in the traditional statistical manner, we are able to describe patterns in the data that are crucial to the theories being tested. Application of non-parametric methods enables us to find regularities in the behavior unknown until now.

Considering Quarterly Earning Announcements for individual stocks and classifying them by market capitalization we find evidence of different behavior among them depending on the stock size. For large and medium stocks there is arrival of new information before announcements to the market, this is not true for the small ones. Trading volume peaks the day of the announcement as a consequence of the revealed information. We also show how changes in prices induce trading volume around zero return in an approximately symmetric fashion. Bad as well as good news (positive and negative returns) produce trading. The joint density of returns and trading volume is approximately symmetric around zero return and is asymmetric around the mode in the turnover dimension. The joint density on the announcement day has fatter tails that any other day. The length of the tails is similar across days.

The novelty of the study completed in the second chapter is not only the data base as it was in the first chapter but also the employed methods as well as most of the conclusions. Some of them were already known in theory but the novelty of several patterns, completly unknown before, makes them an excellent reference for future developments.

The last chapter, co-writen with Ludwig Chincarini, and titled *Differenciating Between Volume and Return Information on Individual Stocks*, has a complete different flavour to the first two. In the previous two chapters we had some theoretical model from which we obtained the structural specification, particularly in the first one. Risk at each moment of time was known and volume was important for its correlation with other unobserved variables causing the trading in the markets. Volume represented the flow of information to the market.

In this chapter we lose control of the risk involved at each point of time but we gain flexibility in the specification. Our results will be related to the covariances of price and volume either joint covariance or individual covariance for different lag periods and in a non-linear way dictated by the particular specification. The methodology used in this part is to specify some trading strategies based on the results of several theoretical models trying to test them with this particular technique. The gain in flexibility will allow us to address the importance of the information contained on trading volume per se. The particular specification of the trading strategies also provides a way to test for the identification function in price reversals attributed to trading volume in some theoretical models. We find evidence about the information impounded in volume and its difference from that of return information. For all stocks, independently of the trading volume, we find price reversals as the contrarian trading strategy literature has already documented.

The major novelty of this last chapter is the informative content of trading volume and its difference from that in prices. This result is specific to the situation where we can not control for the risk; therefore, it will have theoretical implications only to the extent that they provide restrictions on economic models that must be consistent with the empirical results.

Chapter 2

Autocorrelation in Returns and Trading Volume on Individual Stocks

2.1 Introduction

There is a considerable theoretical literature that studies the relationship between the price process of a stock and its relationship to trading volume. In either of the two main approaches (rational expectations or differences of opinions), most of the times the inclusion (consideration) of trading volume is a key element to identify some implications for the time series behavior of returns.

The empirical literature on stock market volume is extensive see Karpoff (1987) for a survey. Typically either the relationship between volatility and volume of trade or the behavior of volume around announcements is studied. There is little work relating serial correlation of stock returns to the level of volume. Most of the papers which do study serial correlation and volume use aggregate data. Morse(1980) studied the serial correlation of returns in high-volume periods for 50 individual securities. He found that high-volume periods tend to have positively autocorrelated returns, but he does not compare high-volume with low-volume periods. LeBaron (1992a) and Sentana and Wadhwani (1992) show that the autocorrelations of daily stock returns change with the variance of returns. Duffee (1992) studied the relationship between serial correlation and trading volume in aggregate monthly data while LeBaron(1992b) used non-parametric methods to characterize the same relation but with daily data. Conrad, Hameed, and Niden (1994) using trading strategies studied the relation between individual stocks' return autocorrelations and the trading volume in individual stocks. Campbell, Grossman, and Wang (1993) investigated the relationship between aggregate stock market trading volume and the serial correlation of daily stock returns. They found that for both stock indexes and 32 individual large stocks, the first-order daily return autocorrelation tends to decline with volume.

In this chapter we will empirically address some of the results suggested by the theoretical models about the dynamic relationship between serial correlation of the stocks returns and trading volume for individual stocks, as a consequence of the flow of information contained in the trading volume. Trading volume is considered as a variable that reflects some unobservable characteristics of the trading process. The main finding, as we would expect from theory, is that the relationship between autocorrelation in returns and volume depends upon the size of the stock. This finding is unique in the literature which previously studied this relationship at an aggregate level only.

As we will see, the influence of the volume of trade in the first autocorrelation of stock returns depends upon stocks size. For large stocks it is negative: "...stock return autocorrelations tend to decline with volume...", (as was documented by Campbell Grossman, and Wang (1993) and LeBaron(1992b) for aggregate data, and by Conrad, Hameed, and Niden (1994) for individual heavily traded stocks using contrarian trading strategies). For small stocks it is positive; moreover, the percentage gain in explanatory power of the serial correlation is larger also in this latter case. We will associate these differences with the class of information asymmetry present in different stocks.

These results could be noise because there are some other variables that are simultaneously determined in the market: trading costs and non-trading periods. Upon study of their influence, we conclude that though there is a simultaneity between size, non-trading days and bid-ask spread (i.e. small stocks usually trade less days and have higher bid-ask spreads than big stocks), there is some other kind of information inside the size variable different from the trading phenomenon (turnover or number of non-trading days) or costs related that makes it different. The size variable has a uniquely stable and inverse relationship with the estimated parameters. Therefore, we will associate size with the degree of asymmetric information: small stocks have fewer uninformed trades that large stocks.

The second finding, suggested by Easley and O'Hara(1992), concerns with the relationship between the depth of the market and the bid-ask spread. We find a different pattern in the autocorrelation of stock returns: for small stocks it is negative and for large stocks it is positive.

The rest of the chapter is organized as follows. Section 2.2 reviews the theoretical motivations and explains the methodology of the empirical tests in section 2.4. Section 2.3 describes the data base. Section 2.4 presents and discusses the empirical results classifying the stocks by size. Section 2.5 studies the robustness of the classification by size against possible alternatives: non-trading and costs. Finally, Section 2.6 concludes the chapter.

2.2 Motivation for the Analysis

The theoretical literature that studies asset prices and trading volume can be divided in two branches: *(i)* rational expectations asset pricing models and *(ii)* models based on differences of opinion. Rational expectations models generate disagreement through private information, these models generally involve trading among private informed traders, uninformed traders, and liquidity (or noise) traders[1]. In the second branch of the literature, trading is induced by differences of opinion among traders over the effect of an announcement upon the ultimate performance of the assets in question. Such disagreements can arise either because speculators have different private information or because they simply interpret commonly known data differently[2].

We will focus on the rational expectations models and particularly on the implications of Wang(1992), Campbell, Grossman, and Wang(1993) (hereafter CGW), and Blume, Easley, and O'Hara (1994) (hereafter BEO). CGW explore the relationship between volume and returns by modelling the interactions between liquidity investors and risk-averse expected utility maximizers (that act as market makers). The market makers must be compensated for satisfying the demands of liquidity traders in such a way, that an actual change in price, because of a selling pressure by liquidity traders, should be compensated by a change in the expected return. Volume information helps distinguish between price movements which are due to the release of public information and those which reflect changes in expected returns. Thus, volume get assigned a identification function for the kind of information that causes the change in price. One of the main implications of CGW is that "... price changes accompanied by high volume will tend to be reversed; this will be less true of price changes on days with low volume...". CGW test empirically this relationship between stock market trading volume and the serial correlation of daily stock index returns and also for 32 big stocks returns, finding that stocks returns autocorrelations tend to decline with trading volume.

Wang(1992) develops a model of competitive stock trading in which investors are heterogeneous in their information (actually some investors have superior information than others) and private investment opportunities and rationally trade for both informational and non-informational reasons. He finds results similar to CGW when

[1]Campbell, Grossman, and Wang(1993), Grossman and Stiglitz (1976,1980), Wang (1992), He and Wang (1993), Pfleiderer (1984), Kyle (1985), Blume at al. (1994).

[2]Harris and Raviv (1993), Kandel and Pearson (1992), Varian (1985, 1989).

there is no information asymmetry among investors: volume is negatively associated with the serial correlation in returns. Trading volume is important for its links to the heterogeneity among investors (asymmetry). Wang(1992) shows how different patterns of volume and price-volume dynamics are motivated by different patterns of heterogeneity among investors. He also shows that in general, information asymmetry reduces the negative relationship between volume and serial correlation in returns. When information asymmetry is severe, volume can be positively associated with serial correlations in returns (in contrast to the case without information asymmetry). In this case he claims that uninformed investors can behave like chartist.

BEO develop an equilibrium security trading model in which some "...fundamental information is unknown to all traders and some traders receive signals that are informative of the asset fundamental...". The source of noise in the model is the quality of information, specifically, the precision of the signal distribution. They show that volume provides information about the quality of informed traders' information which cannot be deduced from price alone. That is, if in CGW and Wang(1992) volume was acting as an instrumental variable for identification of the cause in the movements of prices or heterogeneity among investors, in BEO trading volume appears as another variable considered in the learning process of the agents. Thus, sequences of past prices and volume (technical analysis) can be more informative than prices alone. They conjecture that technical analysis may be particularly appropiate for "...small, less widely-followed stocks...", given that these firms tend to have greater uncertainty about their future results and hence have a low prior precision. Moreover, these firms tend to be "...more affected by private rather than by public information, which means that private infomation have higher effects on them...".

Within the branch of rational expectations and asymmetric information, Easley and O'Hara (1992) develop a model of trading that incorporates the interaction of expectations, prices and volume to study the adverse selection problem in repeated trades. They study how trading volume affects the speed of price adjustment to information, and demonstrate how this price effect differs across markets depending on what they call "market depth" ("ability of a market to accommodate large trades"). In their model, markets with small depth (markets with few large uninformed trades) have a higher initial ask and a lower initial bid price (i.e. large initial spread) than markets with high depth. The basic reason is that the risk of trading with an informed trader rises in markets with less uninformed trading, and hence, prices must compensate for this risk. In addition the convergence of prices to the true value of the security will be faster.

With the results of Wang(1992) and CGW about the relation between the autocorrelation and volume of the stocks there is an obvious hypothesis to test: **the different influence of the volume of trade on the serial correlation of stock returns for individual companies depending on the class of information (public or private and asymmetric)**. As a measure of public information, the volume of trade in the whole market is the best candidate, assuming it is some information all the agents are aware of. The individual volume of trade can incorporate two sources of information: "idiosyncratic" (company-specific, which can be unknown to some of the investors) and "systematic" or related to the market performance. For individual stocks we will decompose the individual volume by source using the market volume in order to isolate the idiosyncratic part and use it as a proxy for private information.

The idea that the amount of trading might be correlated with information-based trading is not new; however, until recently there was no theoretical formulation about the structural relationship between the volume of trade and the autocorrelations of the returns and how the information impounded in the trading process could influence the expected returns.

The notion of informed trades "hiding" in the market, demonstrates it is easier for an informed trader to hide his trading on frequently traded stocks. These ideas, together with the conjecture of BEO about the superior importance of past volume for small firms, leads us to **distinguish the grade of asymmetric information by the stock size or market capitalization.** The consideration of stocks by size, is crucial for two reasons. First because of the widely accepted different structure of returns autocorrelations between small and big stocks, and the indices. Second, according to Wang(1992) and BEO(1994), the importance of the volume should be different in both cases, specifically if we consider **small size as proxy for little trading and with few uninformed trades compared to large stocks.** This consideration connects with the claim of Easley and O'Hara(1992) about the size of the initial spread and therefore the possible different structure of serial correlation of the stocks depending on their size.

Thus, to summarize, we will study **the influence of information impounded in the volume of trade (either market or individual volume) on the serial correlation of the stocks returns for individual stocks.** To study the implications of **information asymmetry and its incorporation into prices and volume, we will divide the stocks by size.** We use firm size as a proxy for the potential different rates of flow and sort of information across securities. According to the theory, we expect to find that volume matters and that its influence depends on the size of the stock.

We now examine the variables that will be analyzed and the empirical models used in the chapter to test the hypothesis.

2.2.1 Methodology

There is no single measure of volume agreed upon in the literature. We will follow Cready and Mynatt (1991), who argue that some theories of trading, particularly those based on informational arguments (and especially informational asymmetries), suggest that volume, rather than the number of transactions is the most appropiate measure of trading activity. With trading volume, each transaction is implicitly weighted by it size (i.e. large block transactions have a relatively large impact in the market while small transactions have a relatively small impact). The usual measure of volume is called "turnover" (ratio of number of shares traded to number of shares outstanding). With this definition, there is no problem in calculating turnover for an individual stock, however there is no agreement upon how turnover for the market should be calculated. This disagreement suggests the importance of studying the sensitivity of the results to various measures of market volume. Hereafter we refer to turnover as volume unless otherwise mentioned.

The approach we follow in this chapter will be similar to that of CGW but for individual stocks. First, we calculate the first autocorrelation coefficient of the returns process, and after we will introduce in the regressions variables representing the volume of trade. There are three kinds of volume to be considered: market volume, individual volume and the idiosyncratic part of the individual volume (i.e. the residuals of a "market model" regression with individual volume regressed upon market volume).

Thus the first set of regressions we will estimate involves the first order autocorrelation of the returns (Equation (2.1)). This specification will be used as a benchmark for comparisons with the following ones.

$$r_{j,t+1} = \alpha_j + \beta_j r_{j,t}. \tag{2.1}$$

Following the theoretical structural relationships commented in the above section, the next step is add to the first autocorrelations of returns a varible that represents the volume of trade, to know how the correlations get modified when considering the information in the trading volume. Equations (2.2) and (2.3) represent this idea. The different specification of volume across equations is based on the idea that market volume (associated with public information) and individual volume (associated with idiosyncratic and systematic information) have different influences upon the serial correlation of returns. For the individual volume, the idiosyncratic buying or selling presure of the stocks creates a risk that is not present within the aggregate measure (which accounts for the influence of the whole market in the individual stock).

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_{j,t}) r_{j,t}, \tag{2.2}$$

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M) r_{j,t}, \tag{2.3}$$

where:

- $r_{j,t}$ = return of security j on day t.
- $V_{j,t}$ = trading volume of security j on day t
- V_t^M = volume traded in the market on day t.

Price changes and trading volume in securities markets may occur in situations unrelated to information specific to a particular security. For example risk preferences changes as pointed in CGW, or wealth changes. If these kind of events are independent of the release of firm specific information, market factors (both informational and non-informational) affecting individual prices and trading volume may be removed through regression, assuming a linear relationship between them. So, although trading and prices changes due to firm-specific information may not be completely isolated, there is an empirical method to remove the effect of other factors.

Thus, assuming trading volume related to firm-specific information can be isolated to some degree, we have proposed the specification of Equation (2.4), and the subsequent use of the residuals in Equations (2.5) and (2.6).

$$V_{j,t} = \alpha_j + \beta_j V_t^M + RES_{j,t}, \tag{2.4}$$

where:

- $V_{j,t}$ = trading volume of security j on day t.
- V_t^M = volume traded in the market on day t.
- $\hat{RES}_{j,t}$ = residuals of the market model for stock j on day t.

The next two equations deal with the same idea of the influence of the trading volume on the first autocorrelation of the returns but considering two different varibles.

Equation (2.5) can be seen as intermediate between Equation (2.2) and Equation (2.3), given that the residuals should account only for the influence of the idiosyncratic part of the trade, and as we conjecture for the transmision of the asymmetric or private information related to the stock in consideration. Equation (2.6) is a modification of Equation (2.3) where we separate the influence of the idiosyncracy of each stock from the influence of the whole market.

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j R\hat{E}S_{j,t}) r_{j,t}, \tag{2.5}$$

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j R\hat{E}S_{j,t}) r_{j,t}. \tag{2.6}$$

Taking the above specifications and studying the stocks by size, we hope to demonstrate according to the theory, that volume matters and depends on the size of the stocks. This result will allow us to draw some interesting conclusions about the possible sources and transmission of information.

2.3 Description of the Data

The data used in this study come from the Center for Research in Security Prices (CRSP). We analyze the daily series of returns and volume of all individual stocks that have been continually listed on CRSP from July 2, 1962 to December 31, 1992, and do not have more than 20 consecutive days of missing data or more than 20 consecutive days without trading. There are 474 stocks that satisfy these requeriments. We divided them by size in five quintiles taken as reference their market capitalization value in the middle of the sample period.

The choice of the daily sampling was determined by several considerations though we were conscious of the potential biases we could introduce. The sampling theory applied in this case is based on asymptotic approximations, thus a large number of observations is appropiate (if there is no missing data each stock has 7675 observations). Contrary to what happens when working with indices of returns, biases associated with asynchronous prices do not appear, because of the individual study for each stock. But working with daily data involves other complications: bid-ask spread and day of the week.

Infrequent trading and its association with the bid-ask spread and therefore with the existence of negative autocorrelation in the stock returns (Roll's (1984) bid-ask effect) can be a problem in daily data. We will consider the claim of Easley and O'Hara (1992) about the possible influence of the volume of trade on the size of the spread, as an additional proof for its empirical robustness when adding the information conveyed the trading volume. In fact, as we will see, the different structure of autocorrelations depending on the size of the stock, and how does it change when adding the information provided by the trading volume, can be considered as another proof of the informational role of the volume.

Another potential bias documented in several studies of daily data is induced by the "day of the week effect". We will account for this by introducing dummy variables in the regressions in the same style as CGW[3].

There is another reason to use daily data[4], as it is done in most of the studies in this catergory. As we are dealing with the transmission of information into returns, a sampling period longer than the day might not be appropiate because of the speed of the transmission. It is also possible that a sampling period of one day may not be long enough to gather some important facts. Thus the daily data is another compromise because of the lack of evidence about the optimal sample frequency[5].

The first work is to build a measure that represents the market volume. We explain in detail in Appendix I the three alternative ways used to construct the market volume measure to be employed. There is neither a widely accepted measure nor an agreement

[3]The continuous reference to some methodologies used in CGW establish an element for comparing the results in two different scenarios.

[4]We will take the CRSP data after applying the criterion of Appendix I as if it does not induce any other bias, though it is not really true.

[5]The same analysis was conducted using weekly data (Wednesday to Wednesday), but we were not able to get any clear conclusion.

on how it should be built. Though most of the studies use turnover, there are three frequently used measures of turnover used in the literature: turnover calculated from the number of shares, from dollar values, or as the arithmetic mean of the individual turnovers. This confusion leads us to briefly address this problem empirically. To do so, we replicated the results of CGW for all the three different measures, and after for a random sample of individual stocks. Quantitatively as well as qualitatively the results were alike, with slight variations using the arithmetic mean of individual turnovers. Thus we will exclusively work with the turnover calculated from dollar values. Intuitively this measure is most appealing, transanctions are weighted both by the number of shares and by their value, and thus the likelihood of increasing the quality and quantity of the information that is incorporated in this measure.

To remove the variation from the variance of the turnover series (individual and market turnover), we measure turnover in logarithms. The use of the turnover series reduces, but does not eliminate, low frequency variations on the series of volume. Thus following CGW and LeBaron (1992b) we will detrend the log-turnover series by subtracting a 200 days moving average of log-turnover. These transformations need two clarifications: one refers to the number of days to include in the moving average, and the other concerning the problems in dealing with individual turnovers where some values are zero.

For both individual and market turnover we considered two other detrending alternatives: subtract a 100 days moving average and use the first difference of the log-turnover. The results were qualitatively the same. We choose to substract a 200 days moving average to follow closely the methods of CGW.

In order to avoid the calculation of the log-turnover for zero values, we redefined the turnover (individual and market) as: $ln((100 * V_t) + c)$, where V_t is the usual definition of turnover traded on day t, and c is a small constant equal to 0.000255 (to preclude computing the natural logarithm of zero). The value of c is chosen to "maximize the normality" of the distribution of daily trading volume[6].

2.4 Empirical Results

2.4.1 Empirical Method

The main hypothesis of the chapter concerns with the influence of trading volume on the serial correlation of the individual stock returns. Thus, it is natural to first study the patterns in the serial correlation and then examine how the correlations are modified by the introduction of new information.

The addition of the new information in the form of trading volume will be related to either public information represented by the trading volume on the whole market or the individual trading volume representing the idiosyncratic and systematic information of any stock. The tables in Appendix III present the results of the calculated regressions used to test the above ideas.

Each regression is calculated for six different sample periods and the results are presented as the sum of all the individual estimations by quintiles according to the stock capitalization. For each coefficient we report three values: its mean value across all the stocks in the same quintile for the given sample period, the number of coefficients with negative value in the quintile, and the number of estimated parameters less than the mean of the quintile. For the t statistics we report its mean value across the stocks in the quintile, the number of times its absolute value is bigger than 1.64 (the critical value for the 5% confidence interval for one tailed t-test, and 10% for a two tailed test), and the numbers of estimated t statistics less than the mean. In order to calculate the t-statistics, the standard errors were estimated using the White(1980) method to correct for heteroscedasticity[7]. We report the R^2 in the same manner: the

[6]See Richardson, Sefcik and Tompson (1986), Cready and Ramanan (1991) and Ajinkya and Jain (1989) for an explanation.

[7]The standard errors are calculated under the assumption that the individual firm parameters are independent and identically distributed within the market. Since the stocks are likely to have

mean of all the estimated R^2 in the quintile, and the number of estimated statistics less than the mean are presented. The R^2s are adjusted by the degrees of freedom (adjusted R^2).

The consideration of six sample periods within the whole sample is motivated by the possibility that large market moves may heavily influence our results. Some of these break points are the same as in CGW. The sample will be divided in the following subsamples:

1. 7/3/62 through 9/30/87.
2. 7/3/62 through 12/31/74.
3. 1/2/75 through 9/30/87.
4. 7/3/62 through 12/30/88.
5. 7/3/62 through 12/31/92.
6. 1/4/88 through 12/31/92.

The two primary cutoff points are 12/31/74 and 9/30/87. The first date corresponds to the change in the structure of the commissions on the New York Stock Exchange (beginning of flexible commissions); the second date corresponds to the stock market crash of October 19, 1987. The first four sample periods were establish to match those in CGW. The fifth sample is the entire sample period, while the sixth sample is included to study the possible structural change after the crask of 1987[8].

2.4.2 Descriptive Statistics

Tables 2.3, 2.4 and 2.5 in Appendix II report some summary statistics in our overall sample for the market and individual firms respectively, including market capitaliza-

cross sectional correlation among them, the standard errors could be biased in some way. Thus the t-statistics should be considered more as an indicative figure.

[8]Only the results for the fifth sample period (7/3/62 through 12/31/92) are presented due to space constraints. There are not serious differences among sample periods. The results of the regressions for the subperiods are available from the author upon request.

tion, turnover, bid-ask spreads and the number of non-trading days. All reported statistics are based on daily observations over the entire 1962-1992 sample period.

The numbers in Table 2.3 reflect the main characteristics of the market during the whole sample period. The variable denominated number of companies specifies those companies with valid records in CRSP, we refer the reader to Appendix I for details. The market crash on October 1987 is reflected in the maximum values of several variables (number of shares traded, number of dollars traded and turnovers). The minimum values of the variables are near the beginning of the sample period (62/07/03), another widely acceptable fact is that the maximum number of shares and capitalization values are at the end of the sample.

Table 2.4 represents the descriptive statistics for the individual stocks that compose our data base. All reported numbers are averages across the mean average of each individual firm. The figures reflect the fairly diverse sample of securities used in the study, this circumstance is very important for the final conclusion. In the capitalization structure there is a large difference between the mean and median, though not for turnover and the bid-ask spread. So it seems there is a greater symmetry when considering either the turnover or the spread that when considering the market capitalization.

Bid-ask spread (BAS) or proportional bid-ask spread, is calculated for each day (t) and stock (j) as:

$$\text{BAS}_{t,j} = \frac{\text{Ask}_{t,j} - \text{Bid}_{t,j}}{\frac{1}{2}(\text{Ask}_{t,j} + \text{Bid}_{t,j})} * 100.$$

The number of non-trading days (or as we will use at some point the percentage of non-trading days respect to the number of trading days) are those days with valid records in CRSP but for which there were no trade (see Appendix I for an explanation).

Bid-ask spread, turnover and non-trading days for each stock are calculated as the average during the whole sample period using daily data from CRSP. The size variable will be the value of the capitalization in the middle of the sample period[9].

Table 2.5 in the Appendix II represents the correlation between the variables of Table 2.4. As expected there exists a high positive correlation among the number of shares traded, capitalization and amount of dollars traded. The negative correlation between the bid-ask spread and the capitalization reflects the aforementioned relationship between small stocks, few uninformed trades and size of the spreads. The number of non-trading days has a negative correlation with all the variables, except with the mean return that is positive but small.

Perhaps the most surprising result is the positive correlation between the turnover and the bid-ask spread. This result seems to follow the predictions of George, Kaul, and Nimalendran (1994) [10]. A similar result (high trading costs when trading volume is high in intraday data) is found in Foster and Viswanathan (1993), this evidence can be explained neither by Admati and Pfleiderer (1988) nor by Foster and Viswanathan (1990). An intuitive argument for this phenomenon, is as a reaction of market makers who impose higher bid ask spreads as a protection against the fear of being trading against hiding private informed investors.

2.4.3 Empirical Findings

Although we have estimated and present regressions for all stocks in the sample, we comment mostly upon the differences between the first quintile (representing the smallest stocks) and the fifth quintile (the largest stocks). The largest differences are between these quintiles, the others represent an intermediate transition. All the comments in this section refer to the tables in Appendix III.

A.-*First Autocorrelation of Stocks Returns.-*

[9]The correlation between this capitalization and the average capitalization during the whole sample period is 0.96 (see Table 2.5).

[10]Allowing the liquidity trading to be cost elastic in an environment of asymmetric information, they get that the expected volume of trade can increase or decrease, depending upon the sensitivity of liquidity trading to transaction costs.

The general result addressed by other papers about the small amount of autocorrelation is present in our estimations, as Table 2.6 represents. The value of the coefficients in some cases is so small that they could even be dismissed, particularly in the middle quintiles. This fact is also reflected in the small value of the R^2s, where the maximum mean value is 1% of explanation, and its maximum values are in the extreme quintiles.

The signs of the mean of the estimations are different between quintiles. For small stocks it is negative with at least 50% of the estimations less than zero, and also at least 50% of them statistically significant. As the size of the stocks increases, more signs are positive and their absolute value rises. Among quintiles, the number of estimations less than zero decreases as the stock size increases. The least number of negative values appear in the fifth quintile. For the largest companies, at least 50% of the coefficients are positive and also at least 50% are statistically significant. These results are similar across subperiods except 1/4/88-12/31/92 where the mean values are smaller.

That the first autocorrelation of the returns of the individual stocks are small, and in some cases is statistically insignificant is neither new nor surprising. Individual returns contain much more company-specific, idiosyncratic, noise than do indices, making it difficult to detect the presence of predictable components. This idiosyncracy characteristic will cause, as we will see, that the inclusion of more information in the form of some other variables related to it (i.e. individual volume) to improve the results of our regressions.

Nevertheless, the characterization of individual stocks' autocorrelation is an interesting first step towards our final goal: demonstrating the importance of the kind and quality of the information depending on the capitalization. Moreover, since negative serial correlation is a well-known symptom of infrequent trading, we will consider it as another element concerning the class of informational trading, and will allow us to connect with the conclusions of Easley and O'Hara (1992).

B.-*First Autocorrelation of Stocks Returns and Individual Volume.-*

The addition of new information in the form of individual volume should improve the previous results if the conclusions of the theory are satisfied empirically. In theory, individual trading volume represents idiosyncratic and systematic information. A priori we expect to find that the importance of the volume variables depends on the size of the stock. It is widely accepted that there is a high correlation between the performance of the whole market and a group of "representative" securities. These apriories are studied in Table 2.7 which refers to Equation (2.2):

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_{j,t}) r_{j,t}.$$

The first change to note in comparing Tables 2.6 and 2.7 is the large decrease in the mean value of the individual correlation coefficients, mainly for the small stocks (the largest change is greater than 70%) as well as in the number of statistically significative coefficients. Another important result is the increase in the number of estimated negative autocorrelations in the lower quintiles. The estimated the mean autocorrelations for the largest stocks do not change as dramatically. There are only small increases in the mean value of the coefficient. As before, most of the coefficients are positive and statistically significant.

There is a similar change in the structure of the R^2. The mean values increase considerably, with the largest increase for the first quintile. Now we are able explain approximatley 1.5% of the returns, where previously less than 1% was explained. For the large companies, the explanatory percentage also increases, but not as much. As a general observation, the highest mean values are again in the extreme quintiles.

The inclusion of the individual volume confirms the structure of autocorrelations. For small stocks the prediction improves considerably and the number of negative coefficients increase. For large stocks the results are as before. Across quintiles, the major changes are in the extremes. We consider this behavior as additional evidence for the hypothesis of Easley and O'Hara (1992) about the relationship between the bid-ask and the number of informed trades and the stock size.

The difference in the signs of the coefficients on volume across quintiles is another important finding. In the first quintile the mean coefficient is positive with 89% of the coefficients larger than zero. For the fifth quintile, the mean coefficient is negative with 73% of the estimated coefficients less than zero. In the intermediate quintiles the negativity increases with the size of the stock. The coefficients are significant for small stocks roughly 50% of the time and for large stocks roughly 25%.

Though the value of the coefficients for volume are in some cases small and insignificant, the sign pattern of the coefficients is instructive. The sign pattern across quintiles is the first piece of evidence linking asymmetric information (few uninformed trades) and stock size. In line with Wang (1992) and CGW, when there is less asymmetric information (more uninformed trades) as is plausible for the big stocks, there is a negative association between the serial correlation and volume of trade (serial correlation declines with trading volume). For the small stocks serial correlation increases with volume from which we conclude that more trading in these stocks is informationally based.

The results of the serial correlation alone plus the association of returns and volume, seens to support two theoretical theses: the importance of the technical analysis for small securities suggested by BEO and derived in Wang (1992), and the relationship between market depth and the bid-ask spread of Easley and O'Hara (1992).

In comparing Tables 2.6 with 2.7, the largest increases in prediction were among small companies (first quintiles). Thus the addition of new information in the form of volume is more relevant for small stocks. As BEO conjecture, these companies tend to be more affected by private rather than by public information; thus, sequences of prices and volume (technical analysis) can be more informative than prices alone. Similar arguments are made in Wang(1992) who further argues that severe information asymmetry induce uninformed investors to behave like chartists.

The structure of the autocorrelations seems to agree with the non-trading symptom and with some conclusions of Easley and O'Hara (1992). For small stocks, with small market depth, the risk for the market maker of trading with informed traders increases, leading to higher bid-ask spreads. Roll's (1984) model predicts in this case negative autocorrelation. The case for large companies is not so clear, and it looks the estimations go along these lines. Once again it seems that company size is a good proxy for the amount of informational trading.

C.- *First Autocorrelation of Stocks Returns and Market Volume.-*

Market volume is considered in this study as a proxy for public information among investors. If we associate with it the notion of no asymmetric information, following Wang(1992) and CGW, we should expect that stock return autocorrelations tends to decline with market trading volume, or that the coefficient that represents the association between the market volume and return has a negative sign. Estimation of Equation (2.3):

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M) r_{j,t},$$

presented in Table 2.8 gathers the results of the estimations based on the above conjectures.

Comparing Table 2.8 with the previous results for individual volume on Table 2.7, the first signal is the different influence on the regressions as a whole of the market volume compared to the individual volume. Though the value of the estimations mostly increases, and also the R^2s with respect to Table 2.6 (first autocorrelation), it is not so important as it was with the individual volume. The pattern of the coefficients on serial correlation are similar, though there are few changes in their values with respect to the those in Table 2.6.

The pattern of the coefficients on volume again depends on stock size: positive for small stocks and negative for large companies. As before, not more than 20% of the estimations are statistically significant in both extreme quintiles however, within each group the signs continue to have the same pattern. For intermediate quintiles the number of values less than zero increases with the size. A *priori* we would expect as in CGW most of the signs to be negative. Whenever there is a selling pressure in the whole market because of plublic news, there is an increase in the expected future returns. Empirically, we see holds for large, not for small stocks. This fact could point towards the argument that the investors and market makers trust more on the improvement of the future performance of the large stocks than of the small ones when confronting the same shock, or that large stocks overcome much better or are not so sensitive in the long run to the news in the market.

D.- *Market Model for Volume.-*

As in the case of returns, there is no theory that justifies Equation (2.4) as the equation for the market model for volume. Nevertheless, as explained Section 2, practitioners have used the model because of its intuitive appeal and because it is the simplest way to account for the influence of the market upon individual companies. We will define the residuals of the market model as the idiosyncratic part of individual volume.

The market volume explains on average between 5% and 15% of individual volume (Table 2.9). Its highest explanatory power is among the largest stocks. Correspondingly, market volume explains small company volume poorly; thus we conclude that company specific information is more important in the small companies. These results match with those from the estimation of Equation (2.3) where we found a different relationship with the market of both classes of stocks.

The coefficients are close or greater than one and statistically significant. Approximately 50% of them are higher than one in the low quintiles and less than one in the upper quintiles. This fact points toward the different reaction of both groups of stocks to movements in the market volume. Thus, though the market explains a higher part of the large stocks individual volume, their sensitivity to changes in the market volume is less than for smaller stocks.

E.- *First Autocorrelation of Stocks Returns and the Residuals of the Market Volume Model.-*

The idiosyncratic component of individual volume for each company is the residual of the regression of individual volume on market volume Equation (2.4). Considering the small percentage of individual volume explained by the market, *a priori* the results of the regression using Equation (2.5): $r_{j,t} = \alpha_j + (\beta_j + \gamma_j R\hat{E}S_{j,t})r_{j,t}$, and presented in Table 2.10 should be, and are, quite similar to the regression in which total individual volume, not idiosyncratic volume, is a regressor (Equation (2.3)).

Looking at the results on Table 2.10, there are only some minor variations that seem normal after the filtration of the individual volume with the market model regression. Again similar comments apply to this scenario, but with the difference that now we are dealing only with the idiosyncratic part of the individual volume.

F.- *First Autocorrelation of Stocks Returns, Market Volume and the Residuals of the Market Volume Model.-*

The joint consideration of the market and company specific information about volume into the regression is the last step in our analysis. As previously mentioned we associate the market volume with the public information. The main motivation for this specification is to examine how different is the information impounded in the company specific volume from that on the whole market when considering both variables at the same time. In order to do that we will estimate Equation (2.6): $r_{j,t} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j R\hat{E}S_{j,t})r_{j,t}$, and present the results in Table 2.11.

As it happened with all the other cases, the R^2s rise considerably, compared to their initial values in Table 2.6. For the smallest stocks the increase is approximately 53%, and for the largest stocks it is around 28%. Again the maximum gains are in the extreme quintiles, and particularly for the small stocks. Once again it seems that the trading volume of the small stocks carries information more important for the autocorrelation of the returns that the volume of the large stocks.

The coefficients representing the serial correlation are similar to those in Table 2.7 (with individual volume, corresponding to Equation (2.2)), though the means are slightly different. Their sign structure remains negative for small companies and positive for big companies.

The association between the market volume and the returns is practically the same as it was in Table 2.8 (from Equation (2.3)): positive sign for small stocks becoming negative as the size increases. The same results and comments apply to the association between the residuals of the market volume and the individual returns. They seem to point again in favor of the argument that the trade of small firms is more informative for the autocorrelation of returns.

Thus, there are not important qualitative differences in the results of this specification (Equation (2.6)) with respect to the others in which only one variable of volume at a time was considered (Equation (2.3) or Equation (2.5)). The reason is the different and apparently independent information they represent: company specific and market related respectively. Comments made previously thus continue to apply here.

2.5 Size, Non-Trading and Costs

In Section 2.4, we associated the signs of the coefficients with the stock size. Following Wang(1992) and CGW we concluded that this is the result of higher information asymmetry in small stocks. There are however some other variables that can influence this result (introducing noise), or even cause it, i.e. trading activity and transaction costs. Thus, there are at least three characteristics (size, trading activity and cost) that could explain our results. There is a simultaneity between them that makes impossible to establish any causal relationship. Thus, and in order to test the robustness of the previous conclusions we will study their relationships with the estimated coefficients of the regressions from Section 2.4.

The size characteristic, as before, will be represented by the value of the capitalization of the stock in the market. Trading activity is going to be associated with either turnover or number of non-trading days. The costs of transaction will be represented by the bid-ask spread[11].

We use turnover as a variable for trading activity instead of number of shares or dollar amount traded for two reasons: (i) to avoid differences across firms because of different number of shares outstanding and prices, and (ii) to keep some stationarity within firms along the sample period. As turnover can be distorted by infrequent but large block transactions, that is why the number of non-trading days can be an alternative measure for trading activity.

The bid-ask spread is usually considered as a proxy for the transaction costs, though some authors also use the capitalization (firm size) as a proxy for it (see Michaely and Vila (1994)), arguing the monotonic decrease in spread with size (both in mean and median) though that is not our case as we will see later.

Taken the estimated parameter values from the regression equations on Section 2.4, we would expect that if firm size serves merely as a proxy for trading activity

[11]The reader is refered to Section 2.4.2 for the definition and statistical characteristics of these variables across stocks.

and there is a liquidity premium for inactively traded shares, then there should be an inverse relationship between the parameter values and trading activity, as it happens with size. Moreover, keeping constant firm size, there should be no relationship between the parameter values and trading activity. However, if differences in trading activity fully explain the firm size effect then no relationship should exist between the parameters and firm size, when trading activity is held constant.

Similarly, if the firm size effect is a proxy for transaction costs, then keeping firm size constant, there should be no relationship between the costs variable and the parameter values. While, if differences in cost explain the firm size effect, then no relationship should exist between the parameters and the firm size when cost is held constant.

Finally, if trading activity is proxy for costs, then keeping constant trading activity, there should be no relation between the costs and the parameter values. Or, keeping constant the costs characteristics, no relationships between trading activity and the parameters should be found.

To explore the above implications we will take the estimated parameter values of the sample period 7/3/62 to 12/31/92, corresponding to Equation (2.6) ($r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j \hat{RES}_{j,t}) r_{j,t}$), the regression with the market volume and the residuals of the marker model for volume (Table 2.11), and study their relationship with the four possible variables candidates to explain their behavior. We choose this particular regression and sample period because of the stability of the coefficients across periods and regressions and because this estimation period has the largest number of observations.

We will sort the stocks according to the four mentioned variables: size, turnover, non-trading days and bid-ask spread and study the characteristic of each classification.

For each sorting criterion we study the following:

- Statistical characteristics of the four variables in each quintile.

- The average of the parameter values and their distribution across quintiles.

- Redistribution of the stocks when changing the criterion of sorting.
- Causal relationship per quintile between the estimated parameters and the four varioables in question.

The reason for analyzing the results by quintile is that in each quintile we can consider that there is one variable that is constant: the variable we are sorting by. By choosing a different sorting criterion, we change the variable to held constant. Therefore, we can study the interactions depending of the redistribution.

In all the tables to be presented and independently of the sorting variable, the first quintile gathers the smallest values of the variable and the fifth the largest values of the variable we are sorting by. All the comments refer to tables on Appendix IV.

A.- *Statistical Characteristics.-*

In this section we are interested in the relationship between the descriptive statistics among quintiles of the four variables depending on the one chosen for sorting. Though from their correlation matrix we were able to infer some relations, there are some others to be discovered in this analysis as we show in Tables 2.12 to 2.15[12].

A priori, it seems natural to associate large stocks with higher trading volume, lower bid-ask spreads and higher trading frequency than small stocks. We can think that these stocks are more followed by the investors than the small ones, thus their information is widely known in the market, therefore most of their trading share similar information. This increases the trading amongst these stocks and thus lower bid-ask spreads, because of the lower probability of trading with investors with private information and because of the fewer number of non- trading days.

The distribution of turnover when sorting by size does not have any special pattern (Tables 2.12 to 2.15). As expected from the correlation analysis, small stocks have more number of non-trading days and higher spreads than large stocks.

[12]These tables use size as the sorting variable. The tables corresponding to the rest of the sorting criteria are not presented for space reasons. They are available upon request.

The intermediate quintiles have higher capitalization (mean and median) when using the turnover for sorting. Also the highest number of non-trading days are in the lowest turnover quintile; and as we already saw in the correlations, there is a direct relation between turnover and bid-ask spreads.

Sorting by number of non-trading days, the direct relation between size and non-trading is again apparent. A new characteristic is the inverse relationship between the number of non-trading days and turnover, not apparent when sorting by turnover. For the bid-ask the only reference is that the quintile with more non-trading days is the quintile with the lowest median bid-ask spread, among others, there is not big differences.

Finally sorting the stocks by the bid-ask spread shows two facts already known: the direct relationship between bid-ask and turnover, and inverse relationship between bid-ask and capitalization. With respect to the non-trading days we have that the lowest bid-ask quintiles has the highest number of non-trading days and the intermediate quintiles the lowest non-trading.

To summarize, we have a monotonic increasing relationship between turnover and bid-ask spread and a monotonic decreasing relationship between size with non-trading days and bid-ask (i.e small stocks trade less days and have higher bid-ask spreads than large stocks). In addition high turnovers are associated with more trading days. Though most of these relationships were present within the correlation matrix, we were not aware of their stability across quintiles.

Thus, it appears, as we expected, that small stocks because of their size could be less followed by the investors than large stocks, and then there is reason to believe that more trading in these stocks is informational based implying high spreads and small trading frequency. This conjecture looks fine when using number of non-trading days as a measure of trading frequency; however is not satisfied for turnover. The direct relationship of turnover with number of trading days and bid-ask spread could be motivated by the "hiding trading" behavior of some informed investors inducing the market makers to act cautiously.

B.- *Averages of the Coefficients.-*

Based on the use of market capitalization as the sorting criterion, in Section 2.4 we concluded that serial correlation tends to decline with trading volume for large stocks and to increase for small stocks. One obvious question is what happens if the sorting variable is not the market size characteristic. How robust are the conclusions? A priori, the theory does not help in identifying the better proxy for the differential informational content, we could find that the results change when changing the proxy. This possibility leads us to compare in Table 2.1 the averages varying the ordering criterion.

As we see in Table 2.1 except when sorting by size or by non-trading days, there is no clear difference between the mean value of the coefficients, the signs and the percentage values in both quintiles, making impossible any clear conclusion. The contrary result obtained when sorting by size or by non-trading days is motivated by their negative correlation and also, as we have already seen, because most of the big stocks do not have any non-trading days.

Looking at the evolution of the number of negative coefficients across quintiles for each sorting criterion (Tables 2.16 to 2.19), only in the size and number of non-trading days classifications we find a monotonic relationship, particularly in the size case.

So, it seems that size and non-trading days are the main candidates to explain the differential behavior of the coefficients. Maybe because they have different informational content, or as it seems, because their simultaneity (large stocks trade almost everyday): size is synonym of trading behavior and trading frequency.

C.- *Cross Classifications.-*

Table 2.1: Average of the Estimated Parameters

The parameter values comes from the regression (Equation (2.6)):

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j R\hat{E}S_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $R\hat{E}S_{j,t}$ = Residuals of the market model on day t.

	# coeff. > 0 (in %)		Mean Values	
	γ	δ	γ	δ
Sorting by Capitalization				
1^{st} Quintile	83	87	0.07552	0.03259
5^{th} Quintile	20	31.9	-0.05794	-0.01221
Sorting by Turnover				
1^{st} Quintile	71.6	65	0.03475	0.01207
5^{th} Quintile	40	50	-0.00671	0.00553
Sorting by Non-trading				
1^{st} Quintile	33.7	38	-0.03273	-0.00753
5^{th} Quintile	73	80	0.06250	0.02018
Sorting by Bid-Ask				
1^{st} Quintile	65	64	0.02385	0.01337
5^{th} Quintile	60.6	70	0.02224	0.02372

The way to read these tables (Tables 2.20 to 2.25)[13] is either by rows or by columns. In either way one variable is changing while keeping the other constant. There are two main messages we can obtain from these classifications: (i) the redistribution of the number stocks among quintiles when changing the sorting criterion, and (ii) the number of coefficients with negative signs and values of the average in their new placements. We are only interested in main patterns.

Considering the cross classifications of size with turnover (Tables 2.20 and 2.21), non-trading days (Tables 2.22 and 2.23) and bid-ask (Tables 2.24 and 2.25), we find again that increasing the size of the stock increases the proportion of negative signs and the average values become negative, independently of the other variables.

Considering the capitalization per quintile (or keeping it "constant") the only relevant information is the redistribution in the number of stocks but not their signs. That is, small stocks have higher number of non-trading days and higher bid-ask spreads than large stocks, but it does not influence in the negativity of the coefficients.

When dealing with the turnover and its relationships with the number of non-trading days and bid-ask spread. For a given level of turnover we find what we already knew, low turnover is associated with more non-trading days and low bid-ask spreads, and contrary for high turnover. An increase in turnover for low non-trading increases the number of negative signs. The same happen for high bid-ask spreads, an increase in the turnover increases the number of stocks and proportion of negative coefficients.

For the cross classification between non-trading days and bid-ask spreads just to mention that independently of the bid-ask, increasing the number of non-trading days decreases the proportion of negative coefficients. We think this is an indirect effect of the size variable (when sorting by non-trading there is a clear direct monotonic relation between non-trading and size).

[13]Only the tables using size as the reference variable are presented. The rest are available from the author.

D.- *Causal Relationships.-*

In this section we are going to study the linear causal relationships between the value of the estimated parameters and the four variables in dispute (size, turnover, number of non-trading days and bid-ask spread). Once again we are looking for some evidence that relates the individual characteristics of the stocks to the value of the estimated coefficients from the structural specifications. Regression analyis will be used as the tool for this purpose.

The general form of the regressions to be estimated will have as independent variable the value of the individual estimated parameters in Section 4 and as dependent variables the value for each stock of the characteristics in consideration (size, turnover, non-trading days and bid-ask spread). That is:

$$\text{Parameter Value}_j = \theta + \zeta * \text{Characteristic}_j. \tag{2.7}$$

In these regressions we focus on the signs and the statistical significance of the estimated ζ coefficients and their signs per quintile. Looking for general patterns among quintiles. Special attention will be placed in the extreme quintiles because it is where there exist major divergences in the sorting variable[14].

Just to mention again that depending on the sorting criterion we can consider a different varible is hold constant per quintile, so it can facilitate our conclusions.

The first table in each sorting criterion is the relation between the sorting variable (reference) and the parameter values. The motivation is to make sure of the constancy of the variable in question.

Given the possible consideration of size as proxy for bid-ask spread (costs), special attention will be place when both variables appear together in the regression function.

As a general view we get the results of Table 2.2 considering all the stocks and

[14]Given the high positive correlation between turnover and bid-ask spread, we will avoid regressions with both variables together.

Table 2.2: Parameter Values and All Variables

The parameter values come from the regression:

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j R\hat{E}S_{j,t}) r_{j,t}$$

$$\text{Parameter Value}_j = \theta + \zeta_1[log(\text{Capit.})_j] + \zeta_2[log(\text{Turnover})_j] + \zeta_3[(\%\ \text{Non-Trad.})_j] + \zeta_4[log(\text{Bid-Ask})_j]$$

ζ_1 (s.e)	ζ_2 (s.e)	ζ_3 (s.e)	ζ_4 (s.e)	R^2
Market Volume				
-0.02951(*) (0.00305)	-0.01721 (0.01878)	-0.00196(*) (0.00089)	-0.03487 (0.03564)	0.16023
RES of Market Model				
-0.00832(*) (0.00112)	-0.01298(*) (0.00362)	-0.00063(*) (0.00030)	0.01621(*) (0.00727)	0.17989

variables together[15] standard errors are in parenthesis.

The signs, when significant[16], are as we would expect: negative for size, turnover and non-trading days; and positive for the bid-ask spread. That is, for small stocks, stocks with low turnover, stocks with more trading days or stocks with high bid-ask spread, the parameter of individual volume becomes more important. For the market volume it seems that the only two relations that matter are the size and non-trading, both negative as well.

But, we should view the above results with care, given the correlations and possible substitutability between the information impounded in some of the variables. Looking at the values of the coefficients when considering as independent variable the variables

[15]Instead of using number of non-trading days we will use the percentage of non-trading days to the total number of days with valid records for each firm. The motivation is the different number of days with valid records across individuals firms because of the missing values.

[16](*) means significative coefficient at 5% level.

used to sort: capitalization, turnover, non-trading days and bid-ask spread (Tables 2.26, 2.31, 2.32 and 2.33 respectively), we observe that the only stable signs and values are capitalization and bid-ask spread. For the turnover and non-trading days either the significance or signs changes. This suggest again that there are some correlations or missing information that disturb the results.

In the turnover case, the value and signs of the coefficients are quite stable, but not their significance. This fact could point towards the redundancy of information that this variable adds to the regression.

Maybe the most remarkable instability corresponds to the non-trading days. Its sign is positive and significative when combining with any variable but capitalization. The instability is also seen across quintiles and depending on the criterion choosen to sort. In any case, the value of the estimated regression coefficients is very small.

Analyzing case by case, we see that when keeping the size (capitalization) constant (Tables 2.26 to 2.30)[17], the only relevant and repetitive relation is with the bid-ask spread for small stocks; there exists a postive relationship between the bid-ask and the value of the parameters for small stocks. That means that for small capitalization the cost matter for individual volume and in a direct relation. The trading activity variables do not matter, except at some point the non-trading in the fourth quintile. So it seems that size has already control for the trading activity and cost, but for small stocks.

Turning to the turnover as a variable of reference, we observe that size matters in most of the cases. Its influence is negative and more important for the market case. This means that trading activity do not fully explains the differences in size. The cost variable (bid-ask) seems to matter only in the higher turnover quintiles in a direct way and when capitalization is not present. For the non-trading case, its instability is again clear. Once more, it appears that size has some kind of information different,

[17] Again only the tables for this sorting criterion are presented. The others are available from the author.

and only bid-ask at some point add some relevance.

Choosing the other alternative variable of trading activity as a way to sort, number of non-trading days, the importance of capitalization is repeated: negative relation with the parameter values, more important for the market volume, and bid-ask spread loses its importance when present. The turnover shows a negative relation when low non-trading and for the residuals of the market model. The bid-ask is significative when size is not present and only for the high non-trading quintiles, where again its relationship is positive with the parameter values. Once again, size appears to be accounting for most of the relevance in our results.

The last studied classification is by cost or bid-ask. A priory, we expect that if size is proxy for cost (as Michaely and Vila (1994) claim) there should be no relation between capitalization and the value of the parameters. However, for all quintiles we find that size is indirectly related to the parameter values. The case of turnover and non-trading days is different. Turnover has an inverse relationship for the highest bid-ask spread stocks only for the residuals of the market model. The number of non-trading days presents a positive relation when is alone or with the turnover, but it is negative and not significative in presence of the size variable. So it seems again, that size already accounts for the non-trading days in some way.

As a summary of the results of the section we find that there is a simultaneity between size, non-trading days and bid-ask spread. This means that small stocks usually trade less days and have higher bid-ask spreads than big stocks. But, there is some other kind of information inside the size variable different from the trading phenomenon (turnover or number of non-trading days) or costs related that makes it different. As we have seen across all the different classifications and sorting criteria, the size variable has a uniquely, stable and inverse relationship with the estimated parameters. Therefore, we associate size with asymmetric information: small stocks have more asymmetric information than big stocks, or maybe better, they have fewer uninformed trades than large stocks.

2.6 Conclusion

In this chapter we have studied the dynamic relationships between the first order autocorrelation in stock returns and the trading volume for individual stocks. We have documented a striking fact about the autocorrelation in individual stock returns: the daily serial correlation of stock returns tends to decline with trading volume for large stocks, and to increase with trading volume for small stocks. Another important finding is the difference in the autocorrelation structure between small and big stocks. These results are robust against the noise or alternative classification introduced by non-trading or costs variables.

We associate these differences with the kind and quantity of informational trading that each class of stocks have. For large stocks, there is more uninformed trading, thus it is less likely to find negative autocorrelated returns. Volume does not carry much more information than prices. For small stocks, the situation is the opposite. Volume is more important, there are fewer uninformed trades, the bid-ask spread increases producing accentuated negative serial correlation in returns, and the return autocorrelation increases with volume. Technical analysis (past prices and volume) can thus be an appropiate approach to study small stocks.

2.7 References

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2.8 Appendix I: The Data Base

The initial data base consist of daily transactions from 62/07/02 (July 2, 1962) to 92/12/31 (December 31, 1992) of all stocks traded on NYSE and AMEX as recorded on the CRSP files (n=7675 observations).

Given some irregularities in the data (described below), we will use each day those records that have valid price, zero or positive volume, positive number of shares outstanding, they are no-ADR's or American Trust ("Americus") and do not have the exchange record code as halted (or suspended).

Irregularities:

- ADR's: For these stocks CRSP records as shares outstanding the number shares worldwide of the company. This figure is wrong for our proposal (we are interested in the portfolio each agent can make with the shares traded inside the USA). To obtain the number of ADR's outstanding available to be traded in the USA by the American investors we consulted the following sources: CRSP, COMPUSTAT, NYSE (several departments), AMEX, MOODY'S, S & P records, ISSM (Institute for the Study of Security Markets, Memphis State University, Memphis, Tennessee), and the SEC Data Base. None of these sources except AMEX have the information on ADR's we were looking for. The AMEX research department have information for eight ADR's currently trading in its Exchange. For the other ADR's it was not possible to get the information. Given these difficulties we decided to drop the ADR's from our calculations.

- AMERICUS TRUSTS (See Jarrow and O'Hara (1989) for an explanation of these instruments): (27 Americus times three divisions each total 81 securities trade) After analyzing the way CRSP accounts for the number of shares outstanding for the primes and scores, and some times for the units we decided to drop them. At some points for several Americus Trust, after transforming everything to units and adding them up, the final result was a greater number of shares outstanding in terms of units than what it was allowed by law. Companies such as Kodak, Merck, Proctor & Gamble, Bristol Meyers Co., Dow, General Electric, Union Pac. were in this category. We talked to the CRSP research department, and they agreed with us about this inconsistency in the accounting. COMPUSTAT has the same figures as CRSP for these stocks, other data bases do not care about the quality of this data because trading on these stocks was canceled in 1992.

- OTHERS:

  1.- HALTED VOLUME: In the CRSP data base there appears some companies for several periods of time (examples: (a) Coradian Corp. CUSIP 21775410 from 84/04/12 to 84/12/31; (b) South Texas Drilling & Expl. Inc. CUSIP 84055310 form 83/03/21 to 83/06/02; (c) Thor Energy Res. Inc. CUSIP 88514810 from 82/01/04 to 82/03/29) where the exchange code was "company halted of trade", though they have valid records for price, volume, returns, and shares outstanding. In this case, if the halt trading is for only one day it could be acceptable because some companies receive the order to cease trading in the middle of the session (that was the explanation of CRSP). However, it is clearly incorrect if trading is recorded as halted for several months and valid parameters (price, volume,...) during this period of time are recorded. CRSP justifies it as a mistake of have not changed the code and suggested to follow the other parameters (price, volume,...). We decided to throw them from the sample given that there is some clear error not well explained by CRSP.

  2.- In the distribution records, CRSP reports splits and dividends, but they do not record other events which may change the number of shares outstanding such as new issues or repurchases by the company of its own securities.

Thus, in constructing the variables that represent the total value of the market either in dollar terms or number of shares or mean of individual turnovers, unlike

CRSP we do not consider: (a) ADR's (CRSP does not include any stock that has "ever been" an ADR, even if its status has subsequently changed); (b) Americus Trust (CRSP has consider them, though after, by telephone, they agreeded about the inconsistencies cited above and their effects (small but present) upon the indices they calculate); (c) if some company has as exchange code "halted for trade" we have also dismiss it (CRSP has included it).

The calculated measures of Turnover are:

- Turnover of company j on day t.

$$V_{j,t} = \frac{n_{j,t}}{N_{j,t}}. \tag{2.8}$$

- Market turnover from number of shares traded on day t.

$$V_t^M = \sum_{j=1}^{T} w_{j,t} * V_{j,t}, \qquad \text{where} \qquad w_{j,t} = \frac{N_{j,t}}{\sum_{j=1}^{T} N_{j,t}}, \qquad \text{and} \qquad \sum_{j=1}^{T} w_{j,t} = 1. \tag{2.9}$$

- Market turnover form dollar values on day t.

$$V_t^M = \sum_{j=1}^{T} w_{j,t} * V_{j,t}, \qquad \text{where} \qquad w_{j,t} = \frac{p_{j,t}N_{j,t}}{\sum_{j=1}^{T} p_{j,t}N_{j,t}}, \qquad \text{and} \qquad \sum_{j=1}^{T} w_{j,t} = 1. \tag{2.10}$$

- Market turnover from the arithmetic mean of individual turnovers on day t.

$$V_t^M = \frac{1}{T}\sum_{j=1}^{T} V_{j,t}. \tag{2.11}$$

  where:

  - $n_{j,t}$ = number of shares traded of stock j on day t.
  - $N_{j,t}$ = number of shares outstanding of stock j on day t.
  - $p_{j,t}$ = price per share traded of stock j on day t.
  - T = number of stocks with valid characteristics on day t.

2.9 Appendix II: Descriptive Statistics

- Table 2.3 Statistics of the Market.
- Table 2.4 Descriptive Statistics for Individual Stocks.
- Table 2.5 Correlation between Variables.

Table 2.3: Statistics of the Market, Daily Data (620703 – 921231, n=7674)

	mean	median	sd. error	max. (date)	min. (date)
# Shares Traded	75459735	29165260	81690447	6.809E8 (871020)	2505660 (621008)
# Shares Outstand.(1000)	38613654	27586418	28241931	1.169E8 (921231)	9332447 (620705)
$ Traded	2.464E9	8.392E8	2.772E9	2.018E10 (871019)	79065209 (621012)
Capitalization (in 1000)	1.261E9	8.164E8	8.770E8	3.783E9 (921218)	3.049E8 (621023)
Turnover (from Shares)	0.001505	0.001262	0.000842	0.009152 (871020)	0.000266 (621008)
Turnover (from Dollar)	0.001460	0.001096	0.000931	0.009988 (871019)	0.000243 (621012)
Mean Turnover	0.001786	0.001749	0.000737	0.008599 (871020)	0.000413 (740812)
# of Companies Used	2368	2356	185.6904	2796 (921228)	1999 (620709)

Table 2.4: Descriptive Statistics for Individual Stocks Fifth Sample Period 7/3/62 – 12/30/92

	Capitalization (in thousands)	Turnover (in %)	# Non-Trading (% inside brac.)	Bid-Ask Spread (in %)
mean	1113,524.5	0.15721	218.3 (2.85)	2.17335
median	303,466.25	0.14190	6 (0.078)	2.00072
st. error	3327,613.4	0.08444	470.9 (6.15)	0.79362
max.	41604,126	0.55520	2652(34.67)	6.74961
min.	1093.75	0.00640	0 (0)	0.86844

Table 2.5: Correlation between the Averages of the Different Variables

	% Non-Trading Days	Return	Shares Traded	$ Traded	Capitali.	Turnover	Capit-77	Bid-Ask
% Non-Trad. Days	1							
Return	0.07476	1						
Shares Trad.	-0.32451	-0.00415	1					
$ Traded	-0.23414	0.01747	0.87310	1				
Capitali.	-0.17605	0.00077	0.81527	0.91514	1			
Turnover	-0.19654	0.05046	0.13343	0.07362	-0.10205	1		
Cap.-77	-0.14353	-0.01444	0.76178	0.84823	0.96245	-0.09190	1	
Bid-Ask	-0.04092	0.07047	-0.05909	-0.09501	-0.14346	0.52455	-0.12396	1

2.10 Appendix III: Estimations

Table 2.6: First Autocorrelation of Stock Returns

$$r_{j,t+1} = \alpha_j + \beta_j r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.

Fifth Sample Period 7/3/62 – 12/30/92

Quintile	$\bar{\beta}$ (# < 0.0) (# < mean)	$\bar{t}$ (#|t| > 1.64) (# < mean)	$\bar{R}^2$ (# < mean)
1 (smallest)	-0.04690	-2.41704	0.00961
($n = 95$)	(64)	(61)	
	(39)	(40)	(68)
2	0.00095	0.06944	0.00509
($n = 95$)	(42)	(72)	
	(43)	(43)	(66)
3	0.01634	0.93427	0.00497
($n = 95$)	(36)	(59)	
	(47)	(47)	(64)
4	0.04468	2.37829	0.00488
($n = 95$)	(22)	(67)	
	(39)	(43)	(58)
5 (largest)	0.05882	3.15748	0.00504
($n = 94$)	(9)	(71)	
	(43)	(45)	(55)
All stocks	0.01469	0.81957	0.00592
($n = 474$)	(173	(330)	
	(207)	(215)	(321)

Table 2.7: First Autocorrelation of Stock Returns and Individual Volume

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- $V_{j,t}$ = Volume traded of stock j on day t.

Fifth Sample Period 7/3/62 – 12/31/92

Quintile	$\bar{\beta}$ (# < 0.0) (# < mean)	$\bar{\gamma}$ (# < 0.0) (# < mean)	$\bar{t}_\beta$ (#|t| > 1.64) (# < mean)	$\bar{t}_\gamma$ (#|t| > 1.64) (# < mean)	$\bar{R}^2$ (# < mean)
1 (smallest)	-0.08349	0.03374	-4.27590	2.20805	0.01439
($n = 95$)	(75)	(10)	(69)	(55)	
	(44)	(49)	(40)	(50)	(67)
2	-0.00678	0.01200	-0.55874	0.74713	0.00631
($n = 95$)	(42)	(36)	(66)	(30)	
	(38)	(53)	(37)	(53)	(66)
3	0.01537	0.00369	0.82650	0.15201	0.00626
($n = 95$)	(38)	(44)	(65)	(35)	
	(41)	(48)	(42)	(48)	(63)
4	0.04711	-0.00366	2.58909	-0.17956	0.00551
($n = 95$)	(23)	(53)	(74)	(26)	
	(38)	(48)	(39)	(47)	(56)
5 (largest)	0.06714	-0.02590	3.98738	-0.63782	0.00583
($n = 94$)	(8)	(69)	(81)	(23)	
	(40)	(40)	(44)	(49)	(55)
All stocks	0.00775	0.00404	0.50634	0.46027	0.00767
($n = 474$)	(186)	(212)	(355)	(169)	
	(195)	(233)	(203)	(267)	(325)

Table 2.8: First Autocorrelation of Stock Returns and Market Volume

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.

Fifth Sample Period 7/3/62 – 12/31/92

Quintile	$\bar{\beta}$ (# < 0.0) (# < mean)	$\bar{\gamma}$ (# < 0.0) (# < mean)	$\bar{t}_\beta$ (#|t| > 1.64) (# < mean)	$\bar{t}_\gamma$ (#|t| > 1.64) (# < mean)	$\bar{R}^2$ (# < mean)
1 (smallest)	-0.05082	0.06913	-2.68305	0.83941	0.01024
($n = 95$)	(66)	(17)	(59)	(19)	
	(39)	(44)	(40)	(44)	(69)
2	-0.00125	0.03123	-0.09802	0.53928	0.00561
($n = 95$)	(44)	(32)	(69)	(19)	
	(42)	(45)	(42)	(55)	(64)
3	0.01646	0.02061	0.99009	0.23864	0.00538
($n = 95$)	(35)	(36)	(65)	(9)	
	(44)	(50)	(46)	(48)	(63)
4	0.04680	-0.01213	2.81769	-0.06734	0.00552
($n = 95$)	(20)	(52)	(73)	(10)	
	(40)	(50)	(44)	(52)	(58)
5 (largest)	0.06306	-0.05399	4.14154	-0.53058	0.00598
($n = 94$)	(7)	(74)	(80)	(2)	
	(40)	(50)	(45)	(52)	(51)
All stocks	0.01475	0.01111	1.02709	0.20543	0.00655
($n = 474$)	(172)	(211)	(346)	(59)	
	(203)	(240)	(209)	(253)	(318)

Table 2.9: Market Model for Volume

$$V_{j,t} = \alpha_j + \beta_j V_t^M$$

- $V_{j,t}$ = Volume traded of stock j on day t.
- V_t^M = Volume traded in the market on day t.

Fifth Sample Period 7/3/62 – 12/30/92

Quintile	$\bar{\beta}$ (# < 0.0) (# < mean)	$\bar{t}$ (#$\|t\|$ > 1.64) (# < mean)	$\bar{R}^2$ (# < mean)
1 (smallest)	1.30799	18.00123	0.04453
($n = 95$)	(0)	(95)	
	(48)	(50)	(55)
2	1.04324	20.05914	0.05430
($n = 95$)	(0)	(95)	
	(38)	(52)	(55)
3	0.94275	23.66431	0.07333
($n = 95$)	(0)	(95)	
	(40)	(48)	(51)
4	0.96089	27.78925	0.09684
($n = 95$)	(0)	(95)	
	(41)	(47)	(50)
5 (largest)	0.94976	35.41184	0.14566
($n = 94$)	(0)	(94)	
	(41)	(46)	(48)
All stocks	1.04112	24.96316	0.08280
($n = 474$)	(0)	(474)	
	(244)	(261)	(279)

Table 2.10: First Autocorrelation of Stock Returns and Residuals of Market Volume Model

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j \hat{RES}_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- $\hat{RES}_{j,t}$ Residuals of the market model on day t.

Fifth Sample Period 7/3/62 – 12/31/92

Quintile	$\bar{\beta}$ (# < 0.0) (# < mean)	$\bar{\gamma}$ (# < 0.0) (# < mean)	$\bar{t}_{\beta}$ (#|t| > 1.64) (# < mean)	$\bar{t}_{\gamma}$ (#|t| > 1.64) (# < mean)	$\bar{R}^2$ (# < mean)
1 (smallest)	-0.08005	0.03190	-4.06134	2.04069	0.01402
($n = 95$)	(75)	(15)	(66)	(53)	
	(43)	(47)	(42)	(51)	(67)
2	-0.00525	0.01042	-0.45598	0.62917	0.00622
($n = 95$)	(41)	(32)	(66)	(22)	
	(38)	(53)	(38)	(54)	(64)
3	0.01550	0.00283	0.75533	0.09178	0.00621
($n = 95$)	(37)	(47)	(62)	(32)	
	(42)	(50)	(43)	(50)	(64)
4	0.04569	-0.00119	2.30843	-0.09802	0.00540
($n = 95$)	(23)	(53)	(70)	(22)	
	(38)	(50)	(42)	(48)	(58)
5 (largest)	0.05952	-0.01337	3.20229	-0.36292	0.00549
($n = 94$)	(10)	(63)	(73)	(17)	
	(40)	(49)	(44)	(52)	(55)
All stocks	0.00697	0.00616	0.34373	0.46188	0.00747
($n = 474$)	(186)	(210)	(337)	(146)	
	(198)	(247)	(198)	(261)	(324)

Table 2.11: First Autocorrelation of Stock Returns, Market Volume and Residuals of Market Model

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j R\hat{E}S_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $R\hat{E}S_{j,t}$ = Residuals of the market model on day t.

Fifth Sample Period 7/3/62 – 12/31/92

Quintile	$\bar{\beta}$ (# < 0.0) (# < mean)	$\bar{\gamma}$ (# < 0.0) (# < mean)	$\bar{\delta}$ (# < 0.0) (# < mean)	$\bar{t}_\beta$ (#|t| > 1.64) (# < mean)	$\bar{t}_\gamma$ (#|t| > 1.64) (# < mean)	$\bar{t}_\delta$ (#|t| > 1.64) (# < mean)	$\bar{R}^2$ (# < mean)
1 (smallest)	-0.08490	0.07552	0.03259	-4.36037	0.92959	2.10634	0.01474
(n = 95)	(76)	(16)	(12)	(71)	(18)	(53)	
	(43)	(47)	(48)	(40)	(49)	(49)	(67)
2	-0.00796	0.03239	0.01099	-0.62709	0.56361	0.67216	0.00674
(n = 95)	(43)	(32)	(33)	(67)	(19)	(25)	
	(39)	(46)	(53)	(38)	(55)	(52)	(65)
3	0.01549	0.02260	0.00266	0.86856	0.23668	0.07312	0.00663
(n = 95)	(37)	(37)	(48)	(67)	(10)	(32)	
	(41)	(54)	(48)	(42)	(52)	(48)	(63)
4	0.04816	-0.01342	-0.00177	2.75504	-0.08643	-0.12276	0.00606
(n = 95)	(23)	(52)	(54)	(76)	(10)	(24)	
	(38)	(50)	(52)	(39)	(51)	(47)	(55)
5 (largest)	0.06662	-0.05794	-0.01221	4.27739	-0.55201	-0.41072	0.00644
(n = 94)	(7)	(75)	(64)	(81)	(3)	(20)	
	(37)	(47)	(49)	(42)	(51)	(51)	(51)
All stocks	0.00736	0.01198	0.00649	0.57491	0.21991	0.46547	0.00813
(n = 474)	(186)	(212)	(211)	(362)	(60)	(154)	
	(196)	(242)	(251)	(201)	(254)	(260)	(323)

2.11 Appendix IV: Robustness of the Estimations

- Table 2.12 Capitalization of Daily Data, Sorted by Capitalization.
- Table 2.13 Turnover of Daily Data, Sorted by Capitalization.
- Table 2.14 Non-Trading Days of Daily Data, Sorted by Capitalization.
- Table 2.15 Bid-Ask Spread of Daily Data, Sorted by Capitalization.
- Table 2.16 First Autocorrelation of Stock Returns, Market Volume and Residuals of Market Model (Sorting by Capitalization).
- Table 2.17 First Autocorrelation of Stock Returns, Market Volume and Residuals of Market Model (Sorting by Turnover).
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- Table 2.20 Cross Clasification, Capitalization vs. Turnover.
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- Table 2.26 Parameter Values and Capitalization (Sorting by Capitalization).
- Table 2.27 Parameter Values and Bid-Ask Spread (Sorting by Capitalization).
- Table 2.28 Parameter Values, Turnover and Percentage of Non-Trading Days (Sorting by Capitalization).
- Table 2.29 Parameter Values, Non-Trading Days and Bid-Ask Spread (Sorting by Capitalization).

- Table 2.30 Parameter Values, Turnover, Non-Trading Days and Bid-Ask Spread (Sorting by Capitalization).
- Table 2.31 Parameter Values and Turnover (Sorting by Turnover).
- Table 2.32 Parameter Values and Percentage of Non-Trading Days (Sorting by Percentage of Non-Trading days).
- Table 2.33 Parameter Values and Bid-Ask Spread (Sorting by Bid-Ask Spread).

Table 2.12: Capitalization of Daily Data, Sorted by Capitalization

	Capitalization (in thousands) Quintile					
	1^{st} (n=95)	2^{nd} (n=95)	3^{rd} (n=95)	4^{th} (n=95)	5^{th} (n=94)	All stocks (n=474)
mean	17,780.17	95,525.95	327,112.17	785,065.22	4376,485.9	1113,524.5
median	17,576.25	89,743.50	307,453.0	780,329.25	2115,852.6	303,466.25
st. error	10,002.49	40,519.16	96,545.58	163,082.63	6518,517.7	3327,613.4
max.	35,814.5	181,086.88	508,711.88	1078,437.5	41604,126.0	41604,126.0
min.	1093.75	37,696.0	182,428.50	516,845.5	1094,011.5	1093.75

Table 2.13: Turnover of Daily Data, Sorted by Capitalization

	Turnover (Turnover*100) Quintile					
	1^{st} (n=95)	2^{nd} (n=95)	3^{rd} (n=95)	4^{th} (n=95)	5^{th} (n=94)	All stocks (n=474)
mean	0.17083	0.14382	0.15436	0.16409	0.15291	0.15721
median	0.15690	0.11820	0.1390	0.1444	0.14495	0.14190
st. error	0.0910	0.08980	0.09325	0.07709	0.06711	0.08444
max.	0.48780	0.41690	0.55520	0.54570	0.390	0.55520
min.	0.03990	0.01650	0.00640	0.01180	0.02210	0.00640

Table 2.14: Non-Trading Days of Daily Data, Sorted by Capitalization

	Non-Trading Days (Percentage values inside braces) Quintile					
	1^{st} (n=95)	2^{nd} (n=95)	3^{rd} (n=95)	4^{th} (n=95)	5^{th} (n=94)	All stocks (n=474)
mean	703 (9.16)	268 (3.49)	67 (0.9)	46 (0.6)	4 (0.05)	218.3 (2.85)
median	511 (6.66)	76 (1)	4 (0.05)	0 (0)	0 (0)	6 (0.078)
st. error	659 (8.60)	452 (5.89)	234 (3.06)	288 (3.77)	20 (0.26)	470.94 (6.15)
max.	2652 (34.67)	2157 (28.14)	1899 (24.80)	2528 (33.12)	185 (2.41)	2652 (34.67)
min.	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)

Table 2.15: Bid-Ask Spread of Daily Data, Sorted by Capitalization

	Bid-Ask Spread Quintile					
	1^{st} (n=95)	2^{nd} (n=95)	3^{rd} (n=95)	4^{th} (n=95)	5^{th} (n=94)	All stocks (n=474)
mean	2.72529	2.10863	2.02061	2.02508	1.98514	2.17335
median	2.60704	1.93535	1.91498	2.00913	1.92480	2.00072
st. error	1.21066	0.83931	0.59371	0.36567	0.34761	0.79362
max.	6.74961	4.47232	4.55734	2.95609	3.18541	6.74961
min.	0.98832	0.86844	1.18004	1.22534	1.40828	0.86844

Table 2.16: First Autocorrelation of Stock Returns, Market Volume and Residuals of Market Model (Sorting by Capitalization)

$$r_{j,t+1} = \alpha + (\beta + \gamma V_t^M + \delta \hat{RES}_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $\hat{RES}_{j,t}$ = Residuals of the market model on day t.

Fifth Sample Period 7/3/62 – 12/31/92

Quintile	$\bar{\beta}$ (# < 0.0) (# < mean)	$\bar{\gamma}$ (# < 0.0) (# < mean)	$\bar{\delta}$ (# < 0.0) (# < mean)	$\bar{t}_\beta$ (#|t| > 1.64) (# < mean)	$\bar{t}_\gamma$ (#|t| > 1.64) (# < mean)	$\bar{t}_\delta$ (#|t| > 1.64) (# < mean)	$\bar{R}^2$ (# < mean)
1 (smallest)	-0.08490	0.07552	0.03259	-4.36037	0.92959	2.10634	0.01474
(n = 95)	(76)	(16)	(12)	(71)	(18)	(53)	
	(43)	(47)	(48)	(40)	(49)	(49)	(67)
2	-0.00796	0.03239	0.01099	-0.62709	0.56361	0.67216	0.00674
(n = 95)	(43)	(32)	(33)	(67)	(19)	(25)	
	(39)	(46)	(53)	(38)	(55)	(52)	(65)
3	0.01549	0.02260	0.00266	0.86856	0.23668	0.07312	0.00663
(n = 95)	(37)	(37)	(48)	(67)	(10)	(32)	
	(41)	(54)	(48)	(42)	(52)	(48)	(63)
4	0.04816	-0.01342	-0.00177	2.75504	-0.08643	-0.12276	0.00606
(n = 95)	(23)	(52)	(54)	(76)	(10)	(24)	
	(38)	(50)	(52)	(39)	(51)	(47)	(55)
5 (largest)	0.06662	-0.05794	-0.01221	4.27739	-0.55201	-0.41072	0.00644
(n = 94)	(7)	(75)	(64)	(81)	(3)	(20)	
	(37)	(47)	(49)	(42)	(51)	(51)	(51)
All stocks	0.00736	0.01198	0.00649	0.57491	0.21991	0.46547	0.00813
(n = 474)	(186)	(212)	(211)	(362)	(60)	(154)	
	(196)	(242)	(251)	(201)	(254)	(260)	(323)

Table 2.17: First Autocorrelation of Stock Returns, Market Volume and Residuals of Market Model (Sorting by Turnover)

$$r_{j,t+1} = \alpha + (\beta + \gamma V_t^M + \delta \hat{RES}_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $\hat{RES}_{j,t}$ = Residuals of the market model on day t.

Fifth Sample Period 7/3/62 – 12/31/92

Quintile	$\bar{\beta}$ (# < 0.0) (# < mean)	$\bar{\gamma}$ (# < 0.0) (# < mean)	$\bar{\delta}$ (# < 0.0) (# < mean)	$\bar{t}_\beta$ (#|t| > 1.64) (# < mean)	$\bar{t}_\gamma$ (#|t| > 1.64) (# < mean)	$\bar{t}_\delta$ (#|t| > 1.64) (# < mean)	$\bar{R}^2$ (# < mean)
1 (smallest)	-0.02057	0.03475	0.01207	-1.08849	0.57197	0.63150	0.00858
(n = 95)	(54)	(27)	(33)	(71)	(14)	(30)	
	(47)	(41)	(45)	(47)	(47)	(42)	(60)
2	-0.00164	-0.00096	0.01208	-0.11167	0.15289	0.67903	0.00660
(n = 95)	(46)	(45)	(34)	(64)	(9)	(33)	
	(44)	(45)	(44)	(44)	(50)	(50)	(65)
3	0.02116	0.01731	0.00111	1.43009	0.21786	0.22235	0.00840
(n = 95)	(27)	(44)	(47)	(80)	(10)	(21)	
	(36)	(55)	(47)	(38)	(57)	(53)	(64)
4	0.02038	0.01530	0.00165	1.40158	0.22441	0.35496	0.00969
(n = 95)	(28)	(40)	(50)	(79)	(13)	(38)	
	(32)	(53)	(51)	(34)	(52)	(58)	(64)
5 (largest)	0.01757	-0.00671	0.00553	1.25016	-0.07064	0.43924	0.00735
(n = 94)	(31)	(56)	(47)	(68)	(14)	(32)	
	(37)	(52)	(55)	(43)	(53)	(58)	(66)
All stocks	0.00736	0.01198	0.00649	0.57491	0.21991	0.46547	0.00813
(n = 474)	(186)	(212)	(211)	(362)	(60)	(154)	
	(196)	(242)	(251)	(201)	(254)	(260)	(323)

Table 2.18: First Autocorrelation of Stock Returns, Market Volume and Residuals of Market Model (Sorting by Percentage of Non-Trading Days)

$$r_{j,t+1} = \alpha + (\beta + \gamma V_t^M + \delta \hat{RES}_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $\hat{RES}_{j,t}$ = Residuals of the market model on day t.

Fifth Sample Period 7/3/62 – 12/31/92

Quintile	$\bar{\beta}$ (# < 0.0) (# < mean)	$\bar{\gamma}$ (# < 0.0) (# < mean)	$\bar{\delta}$ (# < 0.0) (# < mean)	$\bar{t}_\beta$ (#|t| > 1.64) (# < mean)	$\bar{t}_\gamma$ (#|t| > 1.64) (# < mean)	$\bar{t}_\delta$ (#|t| > 1.64) (# < mean)	$\bar{R}^2$ (# < mean)
1 (smallest)	0.05481	-0.03273	-0.00753	3.46436	-0.34813	-0.29478	0.00685
($n = 95$)	(12)	(63)	(59)	(81)	(6)	(23)	
	(33)	(50)	(49)	(40)	(48)	(50)	(60)
2	0.03706	-0.02343	-0.00010	2.31641	-0.17646	0.05798	0.00716
($n = 95$)	(24)	(57)	(49)	(80)	(7)	(24)	
	(34)	(50)	(49)	(38)	(53)	(51)	(61)
3	0.01380	-0.00199	0.00252	0.68673	0.10578	0.19682	0.00532
($n = 95$)	(41)	(45)	(47)	(63)	(10)	(36)	
	(46)	(45)	(47)	(45)	(48)	(49)	(65)
4	-0.02445	0.05606	0.01753	-1.31414	0.66461	1.04988	0.01054
($n = 95$)	(51)	(22)	(37)	(74)	(15)	(34)	
	(44)	(53)	(52)	(45)	(52)	(50)	(66)
5 (largest)	-0.04498	0.06250	0.02018	-2.30917	0.86051	1.32653	0.01079
($n = 94$)	(58)	(25)	(19)	(64)	(22)	(37)	
	(45)	(40)	(49)	(41)	(45)	(52)	(66)
All stocks	0.00736	0.01198	0.00649	0.57491	0.21991	0.46547	0.00813
($n = 474$)	(186)	(212)	(211)	(362)	(60)	(154)	
	(196)	(242)	(251)	(201)	(254)	(260)	(323)

Table 2.19: First Autocorrelation of Stock Returns, Market Volume and Residuals of Market Model (Sorting by Bid-Ask Spread)

$$r_{j,t+1} = \alpha + (\beta + \gamma V_t^M + \delta \hat{RES}_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $\hat{RES}_{j,t}$ = Residuals of the market model on day t.

Fifth Sample Period 7/3/62 – 12/31/92

Quintile	$\bar{\beta}$ (# < 0.0) (# < mean)	$\bar{\gamma}$ (# < 0.0) (# < mean)	$\bar{\delta}$ (# < 0.0) (# < mean)	$\bar{t}_\beta$ (#|t| > 1.64) (# < mean)	$\bar{t}_\gamma$ (#|t| > 1.64) (# < mean)	$\bar{t}_\delta$ (#|t| > 1.64) (# < mean)	$\bar{R}^2$ (# < mean)
1 (smallest)	-0.01338	0.02385	0.01337	-1.02210	0.41729	0.65791	0.00801
(n = 95)	(54)	(33)	(34)	(69)	(10)	(31)	
	(49)	(41)	(44)	(48)	(49)	(43)	(64)
2	0.02802	0.01044	0.00941	1.61188	0.19140	0.46763	0.00655
(n = 95)	(35)	(42)	(33)	(72)	(10)	(28)	
	(43)	(50)	(43)	(46)	(54)	(42)	(54)
3	0.04107	0.00705	-0.00611	2.83351	0.10285	-0.21914	0.00672
(n = 95)	(21)	(48)	(58)	(73)	(11)	(21)	
	(34)	(53)	(52)	(39)	(53)	(52)	(58)
4	0.04757	-0.00359	-0.00776	2.94163	-0.04414	-0.25022	0.00591
(n = 95)	(16)	(52)	(58)	(75)	(11)	(28)	
	(39)	(50)	(47)	(40)	(51)	(50)	(55)
5 (largest)	-0.06728	0.02224	0.02372	-3.53362	0.43443	1.68400	0.01350
(n = 94)	(60)	(37)	(28)	(73)	(18)	(46)	
	(44)	(43)	(50)	(42)	(48)	(53)	(65)
All stocks	0.00736	0.01198	0.00649	0.57491	0.21991	0.46547	0.00813
(n = 474)	(186)	(212)	(211)	(362)	(60)	(154)	
	(196)	(242)	(251)	(201)	(254)	(260)	(323)

Table 2.20: Cross Classification, Capitalization vs. Turnover (Sample Period 7/3/62/ - 12/31/92)

Sorting by Capitalization Quintile		Sorting by Turnover Quintile: Lowest T. 1^{st}	2^{nd}	3^{th}	4^{th}	Highest T. 5^{th}
1 (smallest)						
# stocks	95	20	12	18	17	28
$\bar{\gamma}$	0.07552	0.05967	0.05906	0.07188	0.09871	0.08214
(# < 0.0)	(16)	(3)	(3)	(3)	(2)	(5)
2						
# stocks	95	37	15	9	15	19
$\bar{\gamma}$	0.03239	0.05260	0.06217	0.00981	0.03700	-0.02345
(# < 0.0)	(32)	(6)	(3)	(6)	(4)	(13)
3						
# stocks	95	18	21	23	19	14
$\bar{\gamma}$	0.02260	0.07508	0.02528	0.02753	0.00812	-0.03733
(# < 0.0)	(37)	(5)	(7)	(8)	(7)	(10)
4						
# stocks	95	8	24	22	23	18
$\bar{\gamma}$	-0.01342	0.03138	-0.01986	-0.01430	0.01139	-0.05540
(# < 0.0)	(52)	(2)	(14)	(10)	(11)	(15)
5 (largest)						
# stocks	94	12	23	23	21	15
$\bar{\gamma}$	-0.05794	-0.12011	-0.07769	-0.00247	-0.05693	-0.06437
(# < 0.0)	(75)	(11)	(18)	(17)	(16)	(13)
All Stocks						
# stocks	474	95	95	95	95	94
$\bar{\gamma}$	0.01198	0.03475	-0.00096	0.01731	0.01530	-0.00671
(# < 0.0)	(212)	(27)	(45)	(44)	(40)	(56)

Table 2.21: Cross Classification, Capitalization vs. Turnover (Sample Period 7/3/62/ - 12/31/92)

Sorting by Capitalization Quintile		Sorting by Turnover Quintile: Lowest T. 1^{st}	2^{nd}	3^{th}	4^{th}	Highest T. 5^{th}
1 (smallest)						
# stocks	95	20	12	18	17	28
$\bar{\delta}$	0.03259	0.02662	0.03462	0.02591	0.04492	0.03280
(# < 0.0)	(12)	(1)	(1)	(3)	(3)	(4)
2						
# stocks	95	37	15	9	15	19
$\bar{\delta}$	0.01099	0.01971	0.00348	-0.00996	0.01523	0.00651
(# < 0.0)	(33)	(8)	(6)	(5)	(7)	(7)
3						
# stocks	95	18	21	23	19	14
$\bar{\delta}$	0.00266	0.00520	0.01034	0.00288	-0.00730	0.00106
(# < 0.0)	(48)	(10)	(6)	(12)	(11)	(9)
4						
# stocks	95	8	24	22	23	18
$\bar{\delta}$	-0.00177	-0.00296	0.01833	-0.00695	-0.00334	-0.01974
(# < 0.0)	(54)	(5)	(9)	(13)	(11)	(16)
5 (largest)						
# stocks	94	12	23	23	21	15
$\bar{\delta}$	-0.01221	-0.01540	0.00099	-0.00801	-0.02951	-0.01214
(# < 0.0)	(64)	(9)	(12)	(14)	(18)	(11)
All Stocks						
# stocks	474	95	95	95	95	94
$\bar{\delta}$	0.00649	0.01207	0.01208	0.00111	0.00165	0.00553
(# < 0.0)	(211)	(33)	(34)	(47)	(50)	(47)

Table 2.22: Cross Classification, Capitalization vs. Percentage of Non-Trading Days (Sample Period 7/3/62/ - 12/31/92)

Sorting by Capitalization Quintile		Sorting by Percentage of Non-Trading Days Quintile: Lowest N. 1^{st}	2^{nd}	3^{th}	4^{th}	Highest N. 5^{th}
1 (smallest)						
# stocks	95	1	1	6	28	59
$\bar{\gamma}$	0.07552	0.10546	0.00022	0.03475	0.09289	0.07218
(# < 0.0)	(16)	(0)	(0)	(2)	(1)	(13)
2						
# stocks	95	3	4	20	41	27
$\bar{\gamma}$	0.03239	-0.02889	0.02746	0.01598	0.04144	0.03832
(# < 0.0)	(32)	(2)	(2)	(7)	(12)	(9)
3						
# stocks	95	12	25	35	17	6
$\bar{\gamma}$	0.02260	-0.03767	0.01815	0.00567	0.06866	0.12997
(# < 0.0)	(37)	(8)	(9)	(15)	(4)	(1)
4						
# stocks	95	37	27	23	6	2
$\bar{\gamma}$	-0.01342	-0.02524	-0.00388	-0.00309	0.00538	-0.09901
(# < 0.0)	(52)	(21)	(14)	(12)	(3)	(2)
5 (largest)						
# stocks	94	42	38	11	3	0
$\bar{\gamma}$	-0.05794	-0.04149	-0.07067	-0.07679	-0.05784	0.00000
(# < 0.0)	(75)	(32)	(32)	(9)	(2)	(0)
All Stocks						
# stocks	474	95	95	95	95	94
$\bar{\gamma}$	0.01198	-0.03273	-0.02343	-0.00199	0.05606	0.06250
(# < 0.0)	(212)	(63)	(57)	(45)	(22)	(25)

Table 2.23: Cross Classification, Capitalization vs. Percentage of Non-Trading Days (Sample Period 7/3/62/ - 12/31/92)

Sorting by Capitalization		Sorting by Percentage of Non-Trading Days				
Quintile		Quintile				
		Lowest N. 1^{st}	2^{nd}	3^{th}	4^{th}	Highest N. 5^{th}
1 (smallest)						
# stocks	95	1	1	6	28	59
$\bar{\delta}$	0.03259	0.08738	0.01834	0.01776	0.04502	0.02751
(# < 0.0)	(12)	(0)	(0)	(2)	(4)	(6)
2						
# stocks	95	3	4	20	41	27
$\bar{\delta}$	0.01099	0.02005	0.02225	0.01008	0.00984	0.01072
(# < 0.0)	(33)	(0)	(1)	(10)	(15)	(7)
3						
# stocks	95	12	25	35	17	6
$\bar{\delta}$	0.00266	-0.00750	0.00989	0.00040	0.00527	-0.00133
(# < 0.0)	(48)	(8)	(11)	(15)	(10)	(4)
4						
# stocks	95	37	27	23	6	2
$\bar{\delta}$	-0.00177	-0.00531	0.00078	0.00178	-0.00440	-0.00377
(# < 0.0)	(54)	(21)	(14)	(12)	(5)	(2)
5 (largest)						
# stocks	94	42	38	11	3	0
$\bar{\delta}$	-0.01221	-0.01373	-0.01013	-0.01128	-0.02076	0.00000
(# < 0.0)	(64)	(30)	(23)	(8)	(3)	(0)
All Stocks						
# stocks	474	95	95	95	95	94
$\bar{\delta}$	0.00649	-0.00753	-0.00010	0.00252	0.01753	0.02018
(# < 0.0)	(211)	(59)	(49)	(47)	(37)	(19)

Table 2.24: Cross Classification, Capitalization vs. Bid-Ask Spread (Sample Period 7/3/62/ - 12/31/92)

Sorting by Capitalization Quintile		Sorting by Bid-Ask Spread Quintile: Lowest B. 1^{st}	2^{nd}	3^{th}	4^{th}	Highest B. 5^{th}
1 (smallest)						
# stocks	95	18	10	8	12	47
$\bar{\gamma}$	0.07552	0.07405	0.06782	0.08227	0.10206	0.06979
(# < 0.0)	(16)	(1)	(3)	(2)	(2)	(8)
2						
# stocks	95	32	13	16	11	23
$\bar{\gamma}$	0.03239	0.05421	0.06939	0.05132	0.00685	-0.01985
(# < 0.0)	(32)	(8)	(2)	(7)	(4)	(11)
3						
# stocks	95	24	21	15	23	12
$\bar{\gamma}$	0.02260	0.01509	0.07014	0.03102	0.00852	-0.02910
(# < 0.0)	(37)	(10)	(4)	(5)	(11)	(7)
4						
# stocks	95	13	18	29	28	7
$\bar{\gamma}$	-0.01342	-0.01318	0.00294	-0.01184	-0.02747	-0.00633
(# < 0.0)	(52)	(7)	(7)	(14)	(18)	(6)
5 (largest)						
# stocks	94	8	33	27	21	5
$\bar{\gamma}$	-0.05794	-0.12404	-0.06407	-0.03449	-0.05087	-0.06796
(# < 0.0)	(75)	(7)	(26)	(20)	(17)	(5)
All Stocks						
# stocks	474	95	95	95	95	94
$\bar{\gamma}$	0.01198	0.02385	0.01044	0.00705	-0.00359	0.02224
(# < 0.0)	(212)	(33)	(42)	(48)	(52)	(37)

Table 2.25: Cross Classification, Capitalization vs. Bid-Ask Spread (Sample Period 7/3/62/ - 12/31/92)

Sorting by Capitalization Quintile		**Sorting by Bid-Ask Spread** Quintile Lowest B. 1^{st}	2^{nd}	3^{th}	4^{th}	Highest B. 5^{th}
1 (smallest)						
# stocks	95	18	10	8	12	47
$\bar{\delta}$	0.03259	0.02416	0.02800	0.03254	0.03161	0.03706
(# < 0.0)	(12)	(2)	(0)	(2)	(3)	(5)
2						
# stocks	95	32	13	16	11	23
$\bar{\delta}$	0.01099	0.01629	0.00654	-0.00246	-0.00088	0.02116
(# < 0.0)	(33)	(9)	(3)	(9)	(5)	(7)
3						
# stocks	95	24	21	15	23	12
$\bar{\delta}$	0.00266	0.01219	0.0018[illegible]	-0.00960	0.00203	0.00162
(# < 0.0)	(48)	(9)	(10)	(11)	(10)	(8)
4						
# stocks	95	13	18	29	28	7
$\bar{\delta}$	-0.00177	0.01323	0.01918	-0.00419	-0.02045	0.00119
(# < 0.0)	(54)	(7)	(4)	(17)	(21)	(5)
5 (largest)						
# stocks	94	8	33	27	21	5
$\bar{\delta}$	-0.01221	-0.01882	0.00442	-0.01984	-0.02767	-0.00536
(# < 0.0)	(64)	(7)	(16)	(19)	(19)	(3)
All Stocks						
# stocks	474	95	95	95	95	94
$\bar{\delta}$	0.00649	0.01337	0.00941	-0.00611	-0.00776	0.02372
(# < 0.0)	(211)	(34)	(33)	(58)	(58)	(28)

Table 2.26: Parameter Values and Capitalization (Sorting by Capitalization)

$$\text{Parameter Value}_j = \theta + \zeta[log(\text{Capitalization})_j]$$

The parameter values come from the regression:

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j \hat{RES}_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $\hat{RES}_{j,t}$ = Residuals of the market model on day t.

Quintile	Market Volume (γ) ζ (s.e.)	Market Volume (γ) R^2	RES of Mkt. Volume (δ) ζ (s.e)	RES of Mkt. Volume (δ) R^2
1 (smallest) ($n = 95$)	-0.01372 (0.01016)	0.0081	0.00018 (0.0034)	0
2 ($n = 95$)	-0.00218 (0.04679)	0	-0.02066(*) (0.00653)	0.0745
3 ($n = 95$)	-0.05054 (0.04301)	0.0097	-0.01644 (0.01272)	0.0066
4 ($n = 95$)	-0.07330 (0.04310)	0.01614	-0.02243 (0.01558)	0.0079
5 (largest) ($n = 94$)	-0.0389(*) (0.00797)	0.05078	-0.00276 (0.00594)	0
All ($n = 474$)	-0.02429(*) (0.00260)	0.1452	-0.00789(*) (0.00085)	0.1602

Table 2.27: Parameter Values and Bid-Ask Spread (Sorting by Capitalization)

$$\text{Parameter Value}_j = \theta + \zeta[log(\text{Bid-Ask Spread})_j]$$

The parameter values come from the regression:

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j \hat{RES}_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $\hat{RES}_{j,t}$ = Residuals of the market model on day t.

	Market Volume (γ)		RES of Mkt. Volume (δ)	
Quintile	ζ (s.e.)	R^2	ζ (s.e)	R^2
1 (smallest) ($n = 95$)	0.01507 (0.01711)	0	0.01960(*) (0.00727)	0.07548
2 ($n = 95$)	-0.10610 (0.05951)	0.07086	0.00968 (0.01024)	0.00223
3 ($n = 95$)	-0.05952 (0.03775)	0.01242	0.00586 (0.02087)	0
4 ($n = 95$)	-0.01841 (0.06383)	0	-0.05677(*) (0.02086)	0.07988
5 (largest) ($n = 94$)	0.07726 (0.04879)	0	-0.03843 (0.02062)	0.01945
All ($n = 474$)	-0.00074 (0.02094)	0	0.01698(*) (0.00608)	0.01925

Table 2.28: Parameter Values, Turnover and Percentage of Non-Trading Days (Sorting by Capitalization)

$$\text{Parameter Value}_j = \theta + \zeta_1[log(\text{Turnover})_j] + \zeta_2[(\%\ \text{Non-Trading Days})_j]$$

The parameter values come from the regression:

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j \hat{RES}_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $\hat{RES}_{j,t}$ = Residuals of the market model on day t.

	Market Volume (γ)			RES of Mkt. Volume (δ)		
Quintile	ζ_1 (s.e.)	ζ_2 (s.e.)	R^2	ζ_1 (s.e)	ζ_2 (s.e)	R^2
1 (smallest)	0.01309	0.00028	0	0.00118	-0.00026	0
($n = 95$)	(0.01480)	(0.00101)		(0.00447)	(0.00031)	
2	-0.04287	0.00039	0.02333	-0.00902	-0.00105(*)	0.01060
($n = 95$)	(0.02172)	(0.00202)		(0.00596)	(0.00050)	
3	-0.06613(*)	-0.00566	0.06902	-0.01224	-0.00171	0.00011
($n = 95$)	(0.02097)	(0.00358)		(0.00895)	(0.00136)	
4	-0.03968(*)	-0.00494(*)	0.03487	-0.01805(*)	-0.00092	0.03915
($n = 95$)	(0.01883)	(0.00155)		(0.00741)	(0.00061)	
5 (largest)	0.02526	-0.02700	0	-0.00934	-0.01416(*)	0
($n = 94$)	(0.01950)	(0.02568)		(0.00772)	(0.00691)	
All	-0.00888	0.00362(*)	0.03668	-0.00105	0.00105(*)	0.02797
($n = 474$)	(0.01031)	(0.00081)		(0.00298)	(0.00022)	

Table 2.29: Parameter Values, Non-Trading Days and Bid-Ask Spread (Sorting by Capitalization)

$$\text{Parameter Value}_j = \theta + \zeta_1[(\%\ \text{Non-Trading Days})_j] + \zeta_2[log(\text{Bid-Ask Spread})_j]$$

The parameter values come from the regression:

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j \hat{RES}_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $\hat{RES}_{j,t}$ = Residuals of the market model on day t.

	Market Volume (γ)			RES of Mkt. Volume (δ)		
Quintile	ζ_1 (s.e.)	ζ_2 (s.e.)	R^2	ζ_1 (s.e)	ζ_2 (s.e)	R^2
1 (smallest) ($n = 95$)	0.00024 (0.00099)	0.01656 (0.01830)	0	0.00004 (0.00031)	0.01986(*) (0.00745)	0.06556
2 ($n = 95$)	0.00006 (0.00256)	-0.10562 (0.07393)	0.06070	-0.00027 (0.00045)	0.00776 (0.01149)	0
3 ($n = 95$)	0.00235 (0.00360)	-0.05181 (0.03811)	0.00596	0.00018 (0.00104)	0.00645 (0.02198)	0
4 ($n = 95$)	-0.00407(*) (0.00124)	-0.04822 (0.06940)	0.00311	-0.00129 (0.00045)	-0.06625(*) (0.02337)	0.08750
5 (largest) ($n = 94$)	-0.03797 (0.02166)	0.06549 (0.04972)	0	-0.01226(*) (0.00416)	-0.04223 (0.02161)	0.01644
All ($n = 474$)	0.00394(*) (0.00075)	0.00895 (0.02080)	0.03566	0.00122(*) (0.00021)	0.01998(*) (0.00604)	0.05689

Table 2.30: Parameter Values, Turnover, Non-Trading Days and Bid-Ask Spread (Sorting by Capitalization)

$$\text{Parameter Value}_j = \theta + \zeta_1[log(\text{Turnover})_j] + \zeta_2[(\%\ \text{Non-Trading Days})_j] + \zeta_3[log(\text{Bid-Ask Spread})_j]$$

The parameter values come from the regression:

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j \hat{RES}_{j,t})r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $\hat{RES}_{j,t}$ = Residuals of the market model on day t.

Quintile	Market Volume (γ) ζ_1 (s.e.)	Market Volume (γ) ζ_2 (s.e.)	Market Volume (γ) ζ_3 (s.e.)	R^2	RES of Mkt. Volume (δ) ζ_1 (s.e)	RES of Mkt. Volume (δ) ζ_2 (s.e)	RES of Mkt. Volume (δ) ζ_3 (s.e)	R^2
1 (smallest) ($n = 95$)	0.00898 (0.01861)	0.00037 (0.00104)	0.01164 (0.02282)	0	-0.00721 (0.00551)	-0.00007 (0.00033)	0.02381(*) (0.00868)	0.06864
2 ($n = 95$)	0.00503 (0.08334)	0.00022 (0.00204)	-0.11127 (0.16197)	0.05065	-0.02394(*) (0.00698)	-0.00100 (0.00056)	0.03466(*) (0.01306)	0.07032
3 ($n = 95$)	-0.08851 (0.02937)	-0.00741(*) (0.00374)	0.05534 (0.04505)	0.06836	-0.02909(*) (0.01334)	-0.00302 (0.00158)	0.04167 (0.03011)	0.03276
4 ($n = 95$)	-0.05394 (0.03276)	-0.00459(*) (0.00205)	0.05555 (0.10263)	0.02955	-0.00205 (0.00791)	-0.00131(*) (0.00048)	-0.06229(*) (0.02828)	0.07788
5 (largest) ($n = 94$)	0.01444 (0.02892)	-0.03055 (0.02741)	0.03765 (0.07375)	0	0.00626 (0.01172)	-0.00905 (0.00711)	-0.05430 (0.03214)	0.00789
All ($n = 474$)	-0.01991 (0.01974)	0.00348(*) (0.00084)	0.02998 (0.03614)	0.03848	-0.01374(*) (0.00407)	0.00090(*) (0.00024)	0.03450(*) (0.00747)	0.07914

Table 2.31: Parameter Values and Turnover (Sorting by Turnover)

$$\text{Parameter Value}_j = \theta + \zeta[log(\text{Turnover})_j]$$

The parameter values come from the regression:

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j R\hat{E}S_{j,t})r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $R\hat{E}S_{j,t}$ = Residuals of the market model on day t.

	Market Volume (γ)		RES of Mkt. Volume (δ)	
Quintile	ζ (s.e.)	R^2	ζ (s.e)	R^2
1 (smallest) ($n = 95$)	-0.02519 (0.03329)	0	0.00560 (0.00633)	0
2 ($n = 95$)	0.08176 (0.10520)	0	0.00182 (0.04465)	0
3 ($n = 95$)	0.18032 (0.13469)	0	0.01148 (0.04366)	0
4 ($n = 95$)	0.09270 (0.13296)	0	0.00354 (0.05824)	0
5 (largest) ($n = 94$)	-0.08512 (0.04812)	0.02487	-0.00946 (0.01647)	0
All ($n = 474$)	-0.02156(*) (0.00955)	0.00829	-0.00474 (0.00281)	0.00313

Table 2.32: Parameter Values and Percentage of Non-Trading Days (Sorting by Percentage of Non-Trading Days)

$$\text{Parameter Value}_j = \theta + \zeta[(\%\text{ Non-Trading Days})_j]$$

The parameter values come from the regression:

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j \hat{RES}_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $\hat{RES}_{j,t}$ = Residuals of the market model on day t.

Quintile	Market Volume (γ) ζ (s.e.)	Market Volume (γ) R^2	RES of Mkt. Volume (δ) ζ (s.e)	RES of Mkt. Volume (δ) R^2
1 (smallest) ($n = 95$)	—	—	—	—
2 ($n = 95$)	0.55293 (1.54690)	0	-0.70628 (0.65882)	0.00080
3 ($n = 95$)	0.12853 (0.08994)	0.00821	0.03906 (0.04251)	0
4 ($n = 95$)	0.00363 (0.00935)	0	0.00062 (0.00356)	0
5 (largest) ($n = 94$)	0.00040 (0.00205)	0	0.00022 (0.00034)	0
All ($n = 474$)	0.00388(*) (0.00074)	0.03714	0.00108(*) (0.00021)	0.02980

Table 2.33: Parameter Values and Bid-Ask Spread (Sorting by Bid-Ask Spread)

$$\text{Parameter Value}_j = \theta + \zeta[log(\text{Bid-Ask Spread})_j]$$

The parameter values come from the regression:

$$r_{j,t+1} = \alpha_j + (\beta_j + \gamma_j V_t^M + \delta_j \hat{RES}_{j,t}) r_{j,t}$$

- $r_{j,t}$ = Return of stock j on day t.
- V_t^M = Volume traded in the market on day t.
- $\hat{RES}_{j,t}$ = Residuals of the market model on day t.

	Market Volume (γ)		RES of Mkt. Volume (δ)	
Quintile	ζ (s.e.)	R^2	ζ (s.e)	R^2
1 (smallest) ($n = 95$)	-0.27221(*) (0.06018)	0.13615	-0.00762 (0.02729)	0
2 ($n = 95$)	-0.25548 (0.22701)	0	-0.04845 (0.07433)	0
3 ($n = 95$)	0.67204(*) (0.31081)	0.01634	-0.01370 (0.10194)	0
4 ($n = 95$)	0.11329 (0.15122)	0	0.12275(*) (0.05262)	0.03676
5 (largest) ($n = 94$)	0.11474 (0.07055)	0.01501	0.11759(*) (0.01537)	0.37239
All ($n = 474$)	-0.00074 (0.02094)	0	0.01698(*) (0.00608)	0.01925

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Chapter 3

Price-Volume Behavior Around Announcements: A Non-parametric Approach

3.1 Introduction

The way information (private or public) is reflected in price and volume in financial markets has received much attention lately. In particular, volume has been considered as a measure of the information flow into the market. But, given the different classes of information (private or public, exogenous or endogenous) that can motivate the behavior of the stocks, it is very difficult to establish specific relations between volume and the information flow to the market.

This chapter studies the behavior of trading volume as a measure of the information flow into the market and its relationship with returns for individual stocks. The information flow is related to the nature of information (private or public, exogenous or endogenous). We will consider for the study two trading weeks prior to earning announcements. In this considered period of time there is no regular disclosure of new public information about the stocks, but the investors are expecting it at a given known date in the near future (announcement day). Thus, they have incentives for taking speculative positions to bet on the information to be released based on their private information and the information revealed in the trading process during the previous days. Different classes of information will produce different patterns in trading volume and prices. We assume there are no other regular disclosure of public information during this period of time, but that on the event date.

There is an extensive empirical literature assessing the extent to which returns or trading volume is abnormal in the days surrounding an event[1]. The general conclusion is that there exists an "abnormal" return and volume in the day of the considered event, usually earning or dividend announcements.

There are several theoretical papers that model the behavior of informed agents in the markets[2]. He and Wang (1994) develop a multiperiod rational expectations model of stock trading in which the agents have differential information about the underlying value of stocks. The differential information and multiperiod characteristics allow them to address the connections between volume and the information flow into the market and the way investors' trade can reveal their private information. Because of the dynamic nature of the model they are also able to study the behavior of volume related to informational trading and its relationship to price volatility before public announcements.

The knowledge of forthcoming public announcements will imply an optimal timing of the investors' speculative bets and trading about the information to be revealed, based on their private information and the information revealed through prices. Thus, the pattern of informational trading volume around the announcement depends on the timing of the announcement and the information the investors have or receive during this time. Another interesting conclusion of He and Wang (1994) is the gener-

[1]See for example Beaver (1968), Foster (1973), Morse (1981), Bamber (1986), Kandel and Pearson (1994) for trading volume. See Cready and Mynatt (1991), Brown and Warner (1980, 1985), Stickel and Verrecchia (1992) for returns.

[2]Kyle (1985,1989), Admati and Pfleiderer (1988), Pfleiderer (1984), Kim and Verecchia (1991) and He and Wang (1994).

ation of significant simultaneous price changes (volatility) and high abnormal volume whenever new exogenous information arrives to the investors (in the form of private or public information). Existing private information induces trading but might not induce important changes in prices (volatility).

In this chapter we study two primary empirical implications of He and Wang (1994). First, **we examine the possibility of "non monotonicity" of the informational volume on the days before announcements as a manifestation of the flow of information to the market**, and second **we examine the relationship between the variance in prices and the trading volume during those days.** Another implication we study is the **"higher volume" on the announcement day compared with other days because of the release of new public information**, and its posterior reduction due to the unwind of the speculative positions of the investors after this day. Because of the revelation of public information there should also be an increase in the price variance this day.

We examine price and volume two weeks before and after the anouncement. The consideration of only two weeks before the announcement assures that there is no trading due to public announcements given that there are few revisions of the analyst prediction about stocks made public during this time or any other regular disclosure of information. Studying two weeks after the event allows us to describe the reduction in the speculative positions because of the announcement (though this period can be more complicated to analyze due to the differences between the news and the investors' expectations).

The empirical method to be used is simple non-parametric techniques for regression and density estimation between returns and trading volume for each of the considered days[3]. These methods will allow us to study the characteristics of price and volume day by day, independent of each other, as well as the daily relationship

[3]Gallant et al. (1992) use a seminonparmetric estimate of the joint density function of price changes and volume in a time series context. Härdle (1990), Silverman(1986) and Stoker (1991) are good references for non-parametric methods.

between price and volume without imposing any restriction a priori. We will obtain graphic description of the data that is directly informative of the proposed problem to study.

The main results are as follows. Trading volume, measured as turnover (ratio of number of shares traded to number of shares outstanding), is increasing the days before the announcement for large and medium stocks and approximately constant for small stocks, peaks at the day of the announcement, as a consequence of the revelation of information, and decreases afterwards. There is a positive association between volatility in returns and trading volume before an announcement, mainly for large stocks. This behavior is due to the information revealed to the market by the clearing prices. After an announcement this relationship depends upon stock size. For large and medium stocks there is arrival of new information to investors before the announcement. Changes in returns (either positive or negative) induce trading volume in all stocks. The lowest expected trading volume is around zero return. Thus it seems that trading in stocks is produced by good and bad news. The diversity in returns is greater for small stocks that for large and medium stocks, the turnover is more diverse in large and medium stocks, these stocks have longer tails in the turnover direction. The joint density of returns and trading volume is approximately symmetric around zero return for all the stocks, that is not for the turnover dimension with respect to the mode of the density. The abnormal volume and return on the announcement day documented by other papers seems to be associated with distributions with fatter tails on the event day compared with the surrounding days. The length of the tails is similar across days for a given stock class.

Other related papers are Kandel and Pearson (1993) and Stickel and Verrecchia (1992). Kandel and Pearson (1993) demonstrate the existence of abnormal volume even when prices do not change in response to an announcement. They develop a model in the context of difference of "interpretation of the public signals" by the investors to explain this fact. According to our results, the abnormal volume documented by Kandel and Pearson (1993) can also be motivated by the unwinding of the investors' speculative positions on the announcement day because of the shape of the joint price volume distribution function on this day. Stickel and Verrecchia (1992) study the relationship between the volume of trade in the day of the announcement and the absolute value of the price change. They assume that there exists a proportional relationship between both and test it using data from the day of the announcement, the day before and the day after. Our results suggest that there is a relation between price changes and trading volume but not in a linear form as Stickel and Verrecchia (1992) argue. This relation is almost similar all the surrounding days. This result also matches with Harris and Raviv (1993). They show the existence of positive correlation between absolute price changes and volume in speculative markets when modeling differences of opinion among traders about public news.

There are several differences in this chapter with respect to the mentioned papers. First, we study the dynamic behavior of informational trading volume the days surrounding the announcement as the reflection of the information flow to the market. Second, we focus upon the relationship between price volatility and volume in this period to assess the relationship between the revelation of information in the trading process and the flow of information transmitted to the market. Finally, we describe patterns of behavior around the event day using a non-paramentric approach. This technique avoids imposing any a priori restriction about the "normal" or "abnormal" behavior of any variable or about any relationship among the variables.

The rest of the chapter is organized as follows. Section 3.2 provides the basic setup of the hypotheses to test and how are they going to be tested. Section 3.3 describes the data sources, sample selection and present and discusses the results. Section 3.4 concludes.

3.2 Motivation for the Analysis

Quantifying the information that investors have is a difficult task. We can think there are two kinds of information: exogenous (private or public) and endogenous (generated by the market clearing prices). The arrival of new exogenous information to the market might generate abnormal trading, unlike the case when there is not arrival of new information.

During a period in which there is no new exogenous information and there is an expected public announcement in the near future, investors will speculate about the news to be revealed based on their private information and the endogenous information generated by the market clearing prices. Realized trading volume will be related to the pattern of informational trading and to the timing of the announcement. In this context He and Wang (1994) show that this timing can induce a "non monotonic" pattern of volume before this date peaking on this day. Thus, the first hypothesis to study is **the possible "non-monotonic" evolution of the informational trading volume in the days prior to the announcement, peaking upon the day of the announcement.**

The transmission of information to the market through the prices and its relation with trading volume is another important issue. Studying their joint behavior we can infer the information that is present among the investors at each point in time and how it is revealed in the trading process. Following He and Wang (1994) whenever there is arrival of new exogenous information it produces abnormal volume and it should be accompanied by high price volatility. Trading due to existing private information might not produce increases in price volatility. Thus, we will study the **different relationships between the price volatility and trading volume before the announcement and on the day of the announcement.** Given the nature of the information we hypothesize there exists during the period of consideration, we expect to find a *higher price variance and trading volume on the announcement day than in the surrounding days*, and in the days before the revelation of the information we expect to find that *there are no wide changes in the volatility of prices even when there is trading volume unless there is arrival of new information to investors.*

As a by product of the set up and the techniques to be used, we may also study *the contemporaneous conditional price-volume relationships for each considered day.* This relationship will allow us to address the differential behavior of trading volume depending on the price level and its variability.

Once we have defined the main hypothesis to work with we will describe how they are studied empirically. The first task is to define an announcement. We define an announcement as the revelation or disclosure of some news (information) about the stocks. In order to be public it must be accessible to all investors. In addition, this public disclosure must be periodic, with known periodicity, in order for the investors to have incentives to time their trading strategies and take speculative positions based on their private information.

Another important necessary characteristic is that during the days previous to an announcement there is not systematic release of any public exogenous information[4]. This will ensure that the environment is similar to that analyzed in He and Wang (1994). Before the announcement they consider there is only private information that is revealed through prices in the trading process. The arrival of new exogenous private information will induce instantaneous high trading and price volatility as well as subsequent trading but without price volatility.

Quarterly Earning Announcements have these required characteristics. They have a known periodicity of approximately three calendar months, release some public information about the stocks and are anticipated. Studying only two weeks before the disclosure date we examine an informational environment closest to that considered in He and Wang (1994).

[4] As Kandel and Pearson (1993) point out there are few analysts that publish new updates of their predictions in the two weeks just prior to the earning announcements. This fact implies that during these two weeks the investors might only get new private information (exogenous) and that information revealed by the market clearing prices (endogenous public information) about the stocks.

As a natural extension we also study the reactions of investors after the announcement and their translation to the behavior of prices and volume. The goal is to describe the general patterns after announcements independent of the kind news disclosed, so these results should be taken with care. That is, we do not discuss the pattern conditioning onto the differences between the news and the a priori expectations.

The second task to consider is related to the statistical methodology. Our aim is to use some technique that considering the richness of the data allows convincing demonstration and presentation of the results with a minimum of assumptions. The usual techniques employed in previous studies of this nature is to define some "normal" behavior in some period away before the event and after study the "abnormal" behavior around the announcement based on what it was considered to be "normal" forehand. Though their results are usually intuitive, there is a great discussion about their statistical properties and of their conclusions. Moreover, their only aim is to test and not to describe.

In this chapter we will use simple non-parametric techniques for regression and density estimation. These methods, though not without problems, provide easy graphical description of the data that is informative of the considered problem. Moreover, these techniques allows us to present the data relying minimally on auxiliar economic or econometric assumptions, allowing to describe general patterns. We think that the results compensate by being convincing.

In order to study the daily evolution of volume around announcements accounting for the information disclosed by the prices of the day, we will calculate the daily expectation of the trading volume conditional upon the mean return. To make comparisons between days the mean return will be fixed for all days and equal to the arithmetic mean of the previous and posterior days to the announcement, excluding the day of, before and after the announcement[5]. Assuming a fixed return over all the days

[5]We exclude these days in order not to bias the mean because of the supposed high values during

assures that the results are not due to joint variation of both variables. Moreover, it gives some flavor of what could be "abnormal" volume on the announcement day for a given return value comparing with the surrounding days. The daily evolution of the conditional price variance for a given value of volume will be calculated in a similar manner.

Once we have calculated these variables for each day we use them for graphical and correlation analysis. As a check on robustness, the value of the variable over which we condition on will be changed according to its standard deviation.

As a byproduct of the statistical techniques and sample data, we will be able to study daily expected trading volume conditional on the returns. This analysis is richer than the above daily evolution because now we can account for some important facts about the joint relationships between both variables each day, or as some authors suggest account for the contemporaneous price-volume pressures, before we only had one value per day. The daily analysis of the contour plots of the joint densities for prices and volume will add information about the dispersion around the expected conditional trading volume.

To calculate the conditional expectations we will use a normal kernel and the Nadaraya-Watson estimator. The choice of the bandwidth will follow the recommendations of Stoker (1993) for the conditional expectations and variances, and Silverman (1986) for the estimation of the joint density functions.

the three days. There is also some evidence (see Stickel and Verrecchia (1992) and Kandel and Pearson (1993)) suggesting that in the data base to be used (Compustat) the announcemenent date is not always the date on which the information is first available to investors.

Table 3.1: Descriptive Statistics of the Capitalization (in thousands) per Quintile

	median	mean	standard dev.	maximum	minimum
Smallest stocks (n=209)	26,795.0	28,185.34	17,269.27	60,717.88	2,674.22
Medium stocks (n=209)	380,918.44	400,296.80	131,024.24	666,694.75	206,561.50
Largest stocks (n=209)	4,023,201.3	6,314,011.0	7,628,538.0	75,268,242.50	2,075,456.25

3.3 Empirical Results

3.3.1 Sample Description

The initial sample is composed of those stocks continuously recorded on the CRSP tape traded on the NYSE/ASE from 1981 to 1992 and that have records for the date of the Quarterly Earning Announcements on the Compustat Quarterly Coverage File. The sample period coincides with the availability of the Compustat tapes.

The price variable will be represented by daily returns, and the volume variable by daily turnover, defined as the ratio of number of shares traded over the number of shares outstanding. The stocks will be divided by size in five quintiles taken as reference the value of their market capitalization in the middle of the sample. The study will be done for the first quintile (smallest stocks), third quintile (medium stocks) and fifth quintile (largest stocks).

Table 3.1 presents the descriptive statistics corresponding to the capitalization value in the middle of the sample for the individual stocks that compose the mentioned quintiles. The figures reflect the fairly diverse sample of securities used in the study, this circumstance is very important for the final conclusion. For the smallest and medium stocks there is a great symmetry in the distribution, it is not the same for the largest ones.

Table 3.2: Descriptive Statistics the Days around the Announcements

	Return		Turnover	
	mean	stdev.	mean	stdev.
Smallest stocks	0.000526	0.040211	0.001546	0.002884
Medium stocks	0.000685	0.024686	0.002436	0.003493
Largest stocks	0.000769	0.018692	0.002661	0.002831

In each quintile the stocks will be stacked together by announcement date[6] (refered as "day zero') and we will study the characteristics of the ten trading[7] previous and ten trading posterior days to the announcement in relation to the day of the announcement. Only periods in which there were no other announcements in the considered 21 days for each stock/announcement will be considered. This criterion left 3810 announcements for the large stocks, 3926 for medium stocks and 6639 for small stocks[8].

Table 3.2 presents the means and standard deviations for the turnover and returns for eighteen days (nine days before and nine days after the announcement) per quintile. The choose nine days before and after the announcement is to avoid the distortions caused by the announcement day and the days before and after. These values will be considered in the next section when calculating the conditional expectations and variances. Though the means are small (particularly for returns) and similar for all the stocks, the diversity depends on the variable and stock class: small stocks have the greatest variance for the return and the lowest joint with the large ones for the turnover.

[6]Following the event studies literature we change the time measure from calendar time to event time.

[7]The consideration of ten trading days is to match the two mentioned weeks in which there are not releases of new public information.

[8]To avoid the disturbances produced by outliers we trimmed all those points that were ten or more standard deviations away from the mean turnover, and after those points ten or more standard deviations away from the mean return.

3.3.2 Analysis of the Results

Daily Evolution of Trading Volume

The daily evolution of the expected volume of informational trading is taken to be the expectation of the trading volume conditional upon the arithmetic mean of the returns the days around the announcement ($E(\text{turnover}|\text{mean return})$). For each return value we will obtain one value per day of expected volume. Figures 3-1, 3-2, and 3-3[9] present these expectations for large, medium and small stocks respectively, when conditioning on zero return and plus and minus five times its standard deviation.

The volume profile for small and medium stocks is as expected. There are small relative changes before the announcement until three days before, slightly increasing for the medium stocks. On the event day there is a spike in volume followed by a quick decrease over the subsequent two days, afterwards it has a smooth decreasing pattern, with a minor jump on the sixth day after the announcement. For both small and medium stocks trading volume level is higher after the event date: the news released with the announcement induces higher trading. This pattern matches our hypothesis whenever there is not important new exogenous private information for the agents to modify their expectation but that from the event date. The initial smooth behavior suggests there is not important exogenous news flowing to the market; thus, trading volume is primarily due to the endogenous information transmitted by prices. Three days prior to the announcement investors take speculative positions which are unwond in subsequent trading. For medium size stocks this conclusion changes when studying the mean volume joint with the variance in prices. The higher mean level of trading after than before the announcement can be due to a shift in trading by liquidity traders. If liquidity traders think their information disadvantage is greater before the announcement it is posible that they might shift their trade from before to after the announcement day.

[9] All figures are presented in the Appendix to this chapter.

The volume profile for large stocks is different. There is an increasing pattern of volume before the announcement, peaking the announcement day and decreasing thereafter, with a jump on the sixth day after. The evolution before the announcement is not as smooth as for small and medium stocks, it has a clear increasing trend from the ninth day before until two days before where it jumps as a consequence of the timing in the trading of the investors toward the announcement. This behavior is either a consequence of there is exogenous news flow to the market, the timing strategies followed by the investors toward the release of the information or perhaps there is enough revelation of information in the trading process during these days as to modify the expectations of the investors and not only their speculative positions. This puzzle will be answered when combining with the information on return volatility.

Joint Daily Evolution of Price Volatility and Trading Volume

We calculate price volatility as the variance of returns conditional on a constant value for volume ($Var(\text{return}|\text{mean turnover})$). The constant volume value is the arithmetic mean of the trading volume nine days before and nine days after the announcement[10]. The daily evolution of the profiles are presented in Figure 3-4, Figure 3-5 and and Figure 3-6, representing the evolution of the conditional price variance for large, medium and small stocks respectively, and for several conditioning trading values. According to our hypothesis we expect that if there is no new exogenous private information we should not observe sudden joint changes or swings in the volatility and in the trading volume, except at the announcement date.

Small stocks (Figure 3-6) follows quite close our expectations. Though there are some changes in the volatility of prices they are small and there seems to be neither response in the trading volume nor in its variance (Figure 3-9). Thus it

[10]The conditional variance was also calculated changing the mean volume from a range of values between zero and plus five times its standard deviation, the results were similar patterns. It was impossible to calculate these variances conditioning on the mean minus some multiple of the standard deviation because the value of the conditioning turnover becomes negative.

seems that before announcements there is little incorporation of important exogenous information. However, at the event date, the disclosure of new information increases both variables, decreasing afterwards due to the unwinding of investors' positions.

The profile for large stocks again behaves differently than the rest of the sample. The increasing trend in the conditional volume discussed above is accompanied by a increasing trend with some minor peaks in the variance. As for small stocks the jumps are small in magnitude and with no simultaneity in the estimated mean turnover. Moreover, after the event there is no jump. Again we conclude either there is some new exogenous information arriving to investors before the announcement date or the trading process reveals important information that causes joint increases in both price volatility and trading volume as a consequence in the change of their expectations.

From Figure 3-7, variance of turnover, it is apparent that the revelation of information through the trading is responsible for this increasing pattern. There is another possibility, difficult to test and not present in the other two classes of stocks, relating to the timing of the strategies the investors follow before the announcements. However given the behavior of the estimated mean and variance of the turnover and the variance of the returns, we belive it is the revealed information in the trading process that causes this profile.

The evolution for medium stocks is intermediate that for large and small stocks. The mean turnover has a smooth slightly increasing pattern. The variance in returns (Figure 3-5) is increasing with one swing that peaks eight days before the announcement. There is not a large reaction of the mean turnover on this day. Even if there was arrival of exogenous information to investors that day it was not transmitted to the market immediately, but could have been released afterwards creating the slightly increasing pattern on the trading volume. This hypothesis seems to be plausible when considering the constant variance of the turnover (Figure 3-8) around this day. He and Wang (1994) point out about the possibility of exogenous news inducing trading not only the day of their arrival but some days after, creating the well known autocorrelation structure on the trading volume.

The small peak on the fourth day before the event appears to represent the arrival of new exogenous information to the investors that is transmitted immediately to the market as the mean and variance of turnover indicates, and contrary to what happens in the above discussion. Perhaps the major difference between this day and the one above (eight days before) is that the proximity of the announcement induces the investors to take inmediate actions

The estimated variance of the medium stocks has a greater value the day before the announcement that on this day. It is possible that this is due to mistakes in recording the data; however, the mean and variance for the turnover do not have the same behavior reducing the strength of this argument. It seems possible for the variance of prices to be higher the day before the event because of the timing of the agents in their speculative strategies.

The information content of the announcement is demonstrated by the increase in both price variance and volume for all stocks. Thus, the choice of Quarterly Earning Announcements was right when assuming they have enough informative content. The days after the event have a smooth decreasing pattern of both variables with a peak on the sixth day after in the mean turnover. There is no clear reason for the peak on the sixth day. It could be due to the distribution of the announcements during the week. This hypothesis is rejected later when studying the day of the week in which the announcements are produced.

Taking together the pattern for both variables for the three groups of stocks, we can conclude that the announcements have informational content that is transmitted to the market. The two or three days before there is a monotonic increase in both variables as a consequence of the investors' aggressive bets before the announcement (speculative trading), given their private information. The decreasing and smooth behavior afterwards is a consequence of the unwinding of their positions after the revelation of information. For large and medium stocks it seems there is arrival of new information before announcement leading to jumps in price variance and increasing volume as a consequence of the changes in investors' expectations about the stock value. For small stocks this is not true; it seems the trading is mainly produced by the adjustement of the investors' speculative positions on the stocks because there are not sudden changes in the risks perceived by the investors or in the value of the stock, as would happen with the large and medium stocks. The higher mean trading level after the announcement can be due to a shift in trading from before to after the announcement by liquidity traders to compensate for their informational disadvantages.

The sharp increase in volatility immediately before the announcement and its sharp decrease after this day is a result of the change in liquidity in the market around the announcement. According to He and Wang (1994) before the event there is a decrease in liquidity because of intensive informational trading. Liquidity increases afterwards because of the reduction in uncertainty due to the public information revelation. This decrease in liquidity will increase the sensitivity of the prices to supply shocks, thus increase price volatility.

Contemporaneous Price-Volume Relationships

Previously we have examined the behavior of expected returns and volume around the announcement date as a way to describe the transmission of information to the market. In this section our concern will be the relationship between both variables on a given day. One approach would be to use regression analysis however, given the inherent simultaneity between price and volume and the need to impose a specific functional form, the results might be not accurate. The natural alternative is again to use non-parametric methods calculating conditional expectations. Because of their analogy to a regression function these expectations ($E(\text{turnover}|\text{return})$) will produce two kinds of valuable information, one related to the best functional form to relate both variables, and another concerning their joint behavior. The analysis will be complemented with the contours from the estimated joint density functions between both variables.

There is no theoretical model that studies this relationship becau. it is neither an interday not an intraday relation, it is the product of the supposed con. non behavior of the individual stocks around one event. Again we will differenciate the stocks by size measured by their market capitalization.

The conditional expectation and variance of the trading volume condition on the return is presented in Figure 3-10 for large stocks, Figure 3-11 for medium stocks and Figure 3-12 for small stocks[11]. Representative days before and after the announcement are graphed. The axes are in the same units across days and stocks. Thus it is possible to make all classes of comparisons. Special attention should be given to the horizontal axis which represents the returns. The zero point coincides with a zero return. To mitigate oscilatory patterns in the extremes and to homogenize the graphs across days and stocks we trimed the estimations corresponding to ten or more percentage returns away from zero return and more than one percentage turnover away from zero turnover.

Independent of stock size they have similar shapes on the functional form. All stocks have a U-shape form before the announcement day. After the announcement, the U-shape is still present. The minimum value is always around zero return. The flatter shapes for the small stocks are due to their higher dispersion compared to the other classes of stocks. These patterns suggest that good news (positive returns) as well as bad news (negative returns) induce trading in the stocks even the day of the announcement. Interestingly, Figure 3-10, Figure 3-11 and Figure 3-12 indicate that the direction of the daily change in the trading volume is related to the contemporaneous return but not to its sign because of the almost symmetry around zero return. Trading increases with any deviation to either side of zero returns. Trading

[11]The expected value is the continuous line and the variance the dashed one. The variance is multiplied by one hundred for all the days/stocks.

volatility has the same behavior. Comparing the minimum values across days we can conclude what was already known from Figures 3-1, 3-2, and 3-3 (evolution of expected conditional turnover): the highest minimum is on the announcement day.

The increase in trading volume because of changes in prices in any direction is proved empirically in Stickel and Verrecchia (1992) using a constant factor of proportionality. Harris and Raviv (1993) modeling the differences of opinion among traders shows that absolute prices changes are positively correlated with volume. These two results match with our finding about the joint variation in volume and returns though for us not in a linear form. Their results are also compatible with the lowest trading being around zero return but not the trading for zero return as pointed by Kandel and Pearson (1993).

Though the results of Figure 3-10, Figure 3-11 and Figure 3-12, expected volume conditional on price variability, are interesting, they do not address the question of the variability in the volume at each return level and viceversa. Figures 3-13, 3-14 and 3-15 provide this additional information. Each figure presents estimates of the joint density of returns (horizontal axis) and turnover (vertical axis)[12]. These figures are contour maps: points linked by a contour have the same density and the contours are equally spaced across days and stocks.

The contour plot for small stocks shows less diversity in volume for a given return level than those for large stocks and medium stocks, the contour lines are closely bunched near the mode. This fact is compatible with the common opinion about the lower trading in small than in large and medium stocks. For all the stocks the greatest turnover dispersion is around zero return. The mode is near zero returns for all the stocks and near zero turnover for small stocks but not for large and medium ones. The greater turnover diversity in large and medium stocks causes fatter tails in the volume direction than those in the small stocks, where trading volume is very concentrated.

[12]The axes are in the same units as those in the conditional mean and variance.

All densities are symmetric around zero return, but not around the mode of turnover. Another particularity is the higher dispersion on returns for a given volume level for small stocks, but not for the turnover as it was commented before. Studying day by day the announcement date is peculiar for having similar dispersion for both variables in all the stocks as any other day, but for having fatter but not longer tails than any other day. This phenomenon seems to induce the "abnormal" volume and returns found in other studies. The fatter tails on the event day can either be explained by the differences of opinion among traders about the released news, or in a context of differential of information by the unwinding of the speculative positions of the investors.

There are two potential biases in our results that deserve some attention. The first is related to the influence of the bid-ask spread; the second to the day of the week effects. We do not believe that the bid-ask spread biases our previous results[13], because we are not relating different days with correlation or regression analysis. Even that, our interest is in the relationship between the amount of trading and the return each day, independently of how the returns are measured (bid, ask or in between), the important thing for us is the act of the transaction.

Examination of our sample suggest that announcements are randomly distributed over the five week days. The stack of calendar days among firms makes more random their daily distribution. Table 3.3 presents the days in which the announcements were recorded in the Compustat tape as the event date[14]. Except for large stocks they seem to be equally distributed through the week.

[13]Apart from those introduced by the manner in which CRSP records the data.

[14]Some anouncements produced on holidays (non trading days) were dismissed from the initial sample for obvious reasons.

Table 3.3: Day of the Week for the Announcements

	Smallest stocks	Medium stocks	Largest stocks
Monday	1303	647	462
Tuesday	1294	732	731
Wednesday	1362	858	925
Thursday	1383	994	1021
Friday	1297	695	671
Total	6639	3926	3810

3.4 Conclusion

In this chapter we have studied the behavior of trading volume around announcements as a measure of the flow of information to the market. In addition, we examined the pattern of price volatility around announcements as a measure of the arrival of new information to the market. Volume changes conditional on changes on price for each day were also examined. The main results are as follows.

The days around announcements for all the stocks news (either good or bad) produce an increase in trading. For large and medium stocks new information arrives to the market before the announcement. Trading volume increases gradually until three days before the announcement where it increases rapidly peaking the announcement day, decreasing thereafter. Volatility in returns follows a similar pattern. Small stocks exhibit different behavior. Before the announcement there is no new information arriving to the market, as demonstrated by trading volume and price volatility. The release of information on the announcement day produces a jump in both variables. The information content of the announcement is demonstrated by the peaking behavior of the estimated conditional mean turnover and conditional variance in the returns.

Large and medium stocks have greater diversity in turnover than small stocks, for all of them the greatest turnover dispersion is around zero return. Small stocks have the greatest diversity of returns among the three classes of stocks. The joint density of return and trading volume is approximately symmetric around zero return, it is asymmetric around the mode in the turnover dimension with longer tails for higher turnover values than the mode. The announcement day presents fatter tails that the surrounding days.

3.5 References

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3.6 Appendix: Figures

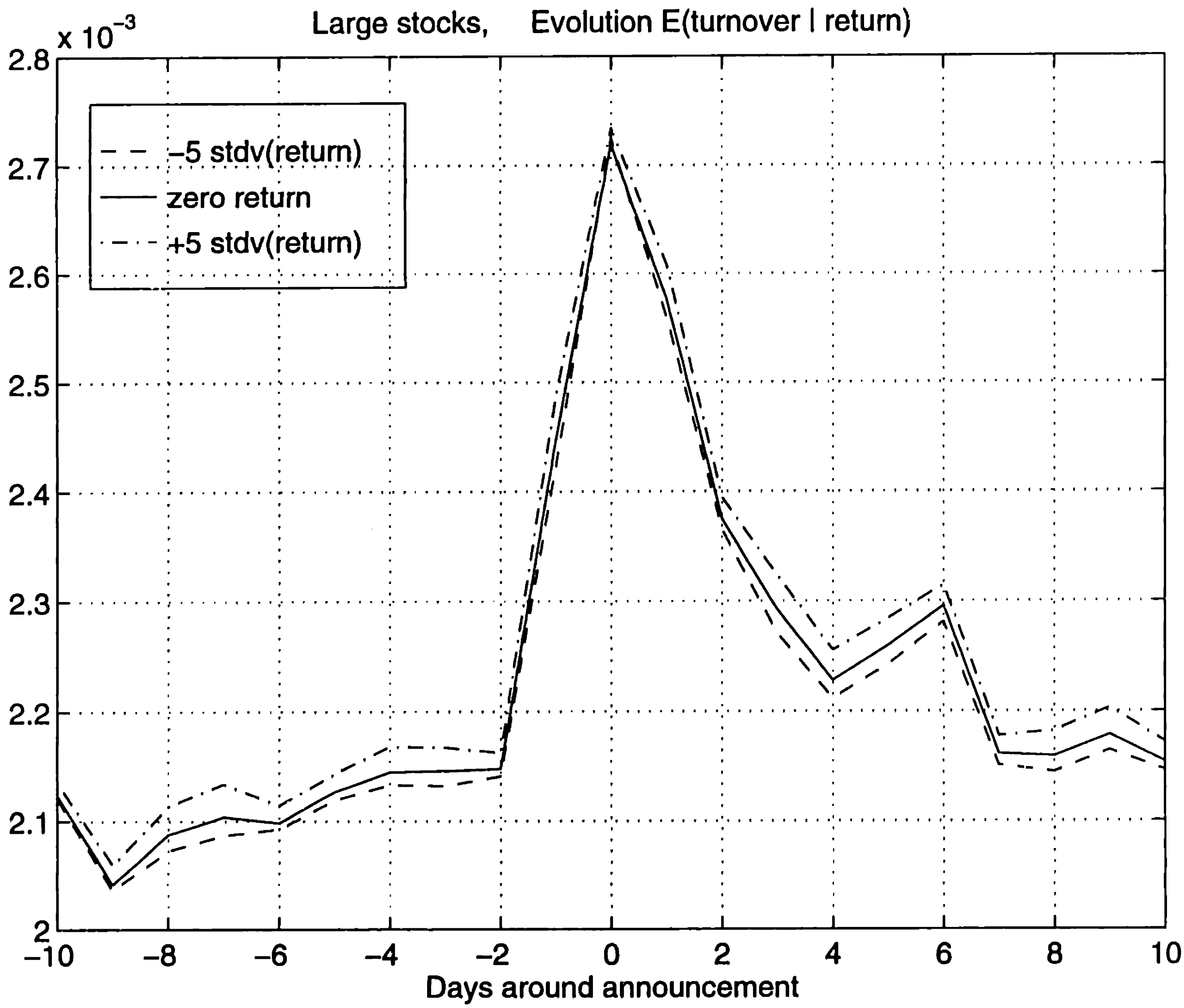

Figure 3-1: Large Stocks: Mean Turnover.

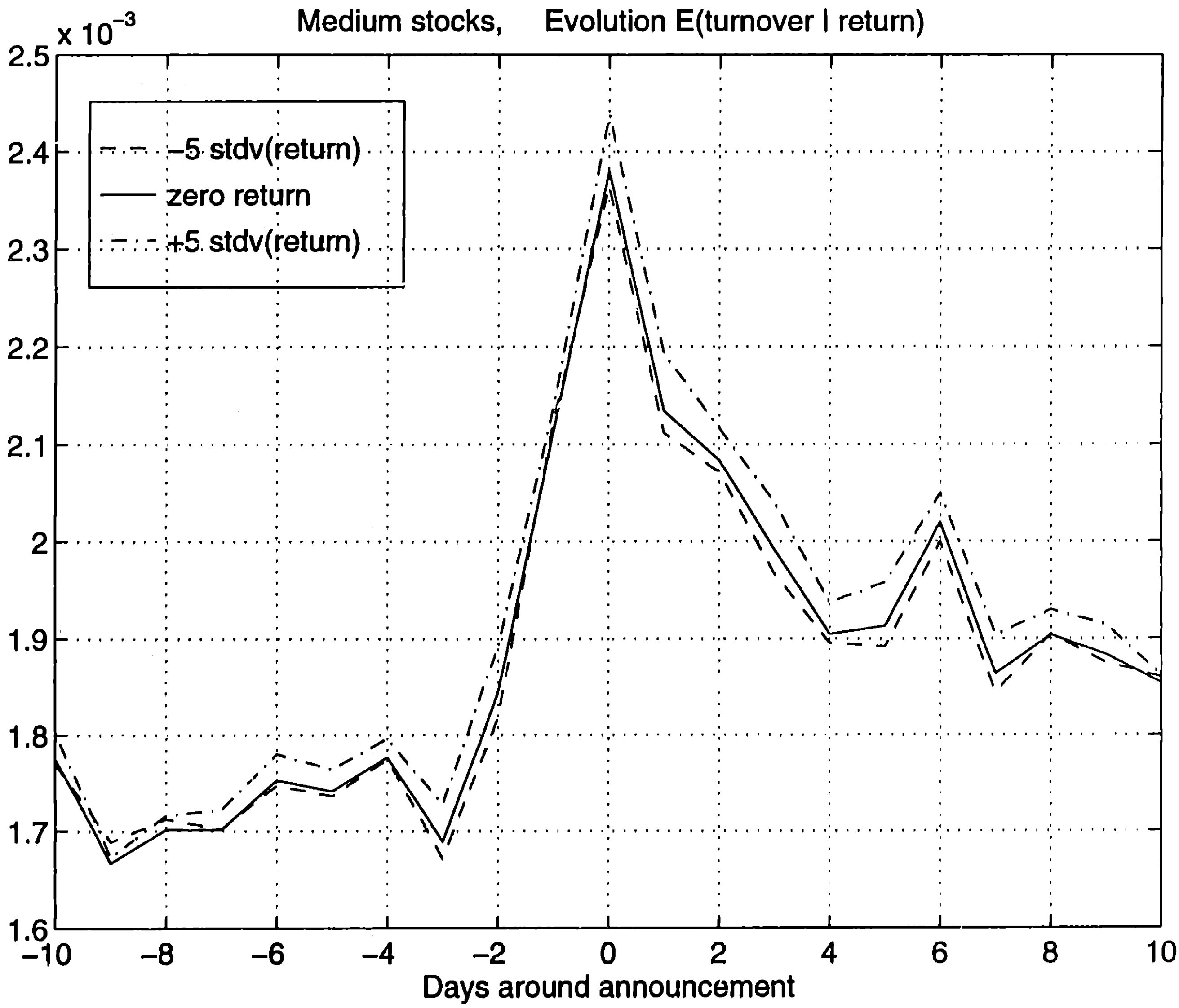

Figure 3-2: Medium Stocks: Mean Turnover.

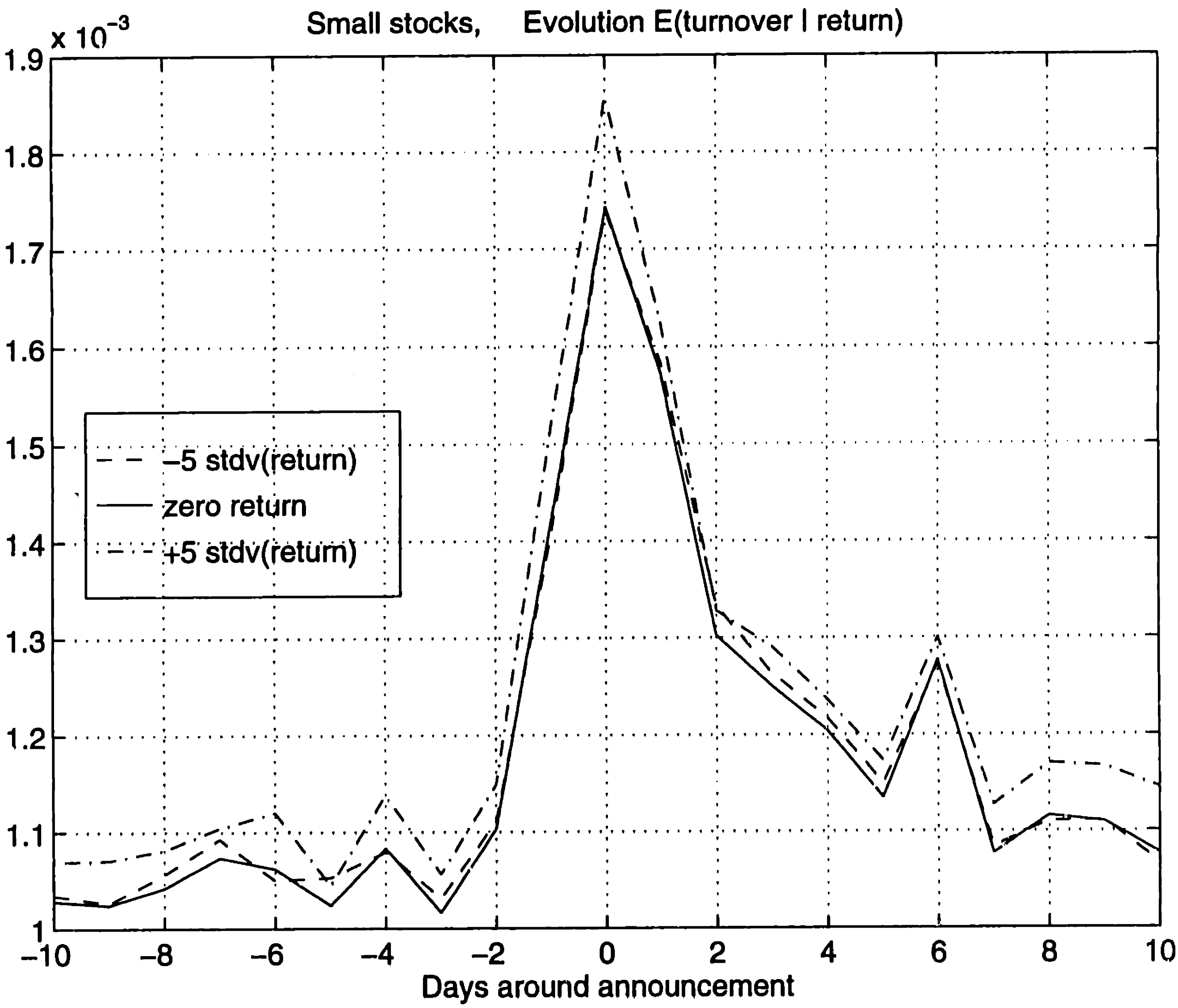

Figure 3-3: Small Stocks: Mean Turnover.

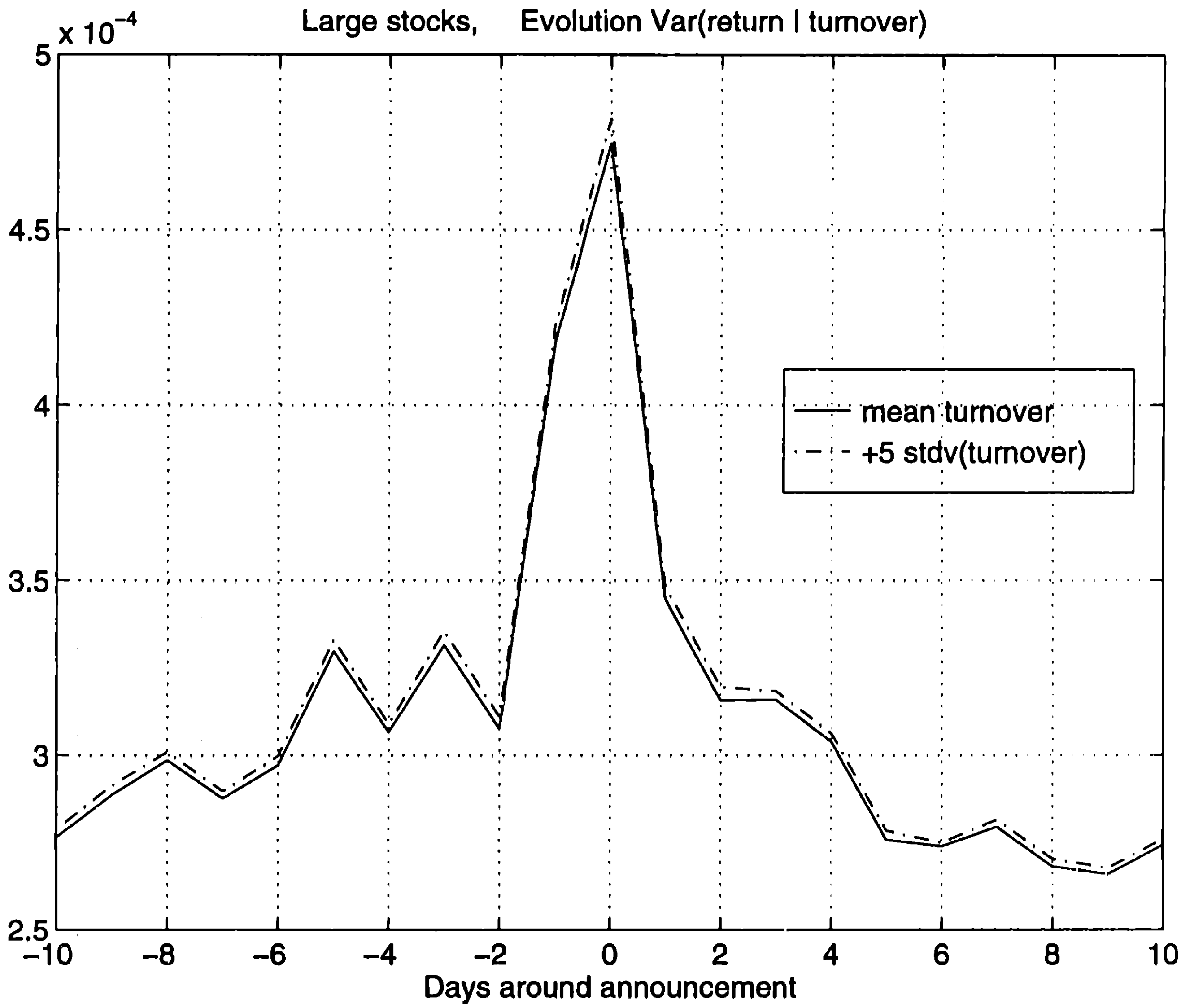

Figure 3-4: Large Stocks: Variance of Return.

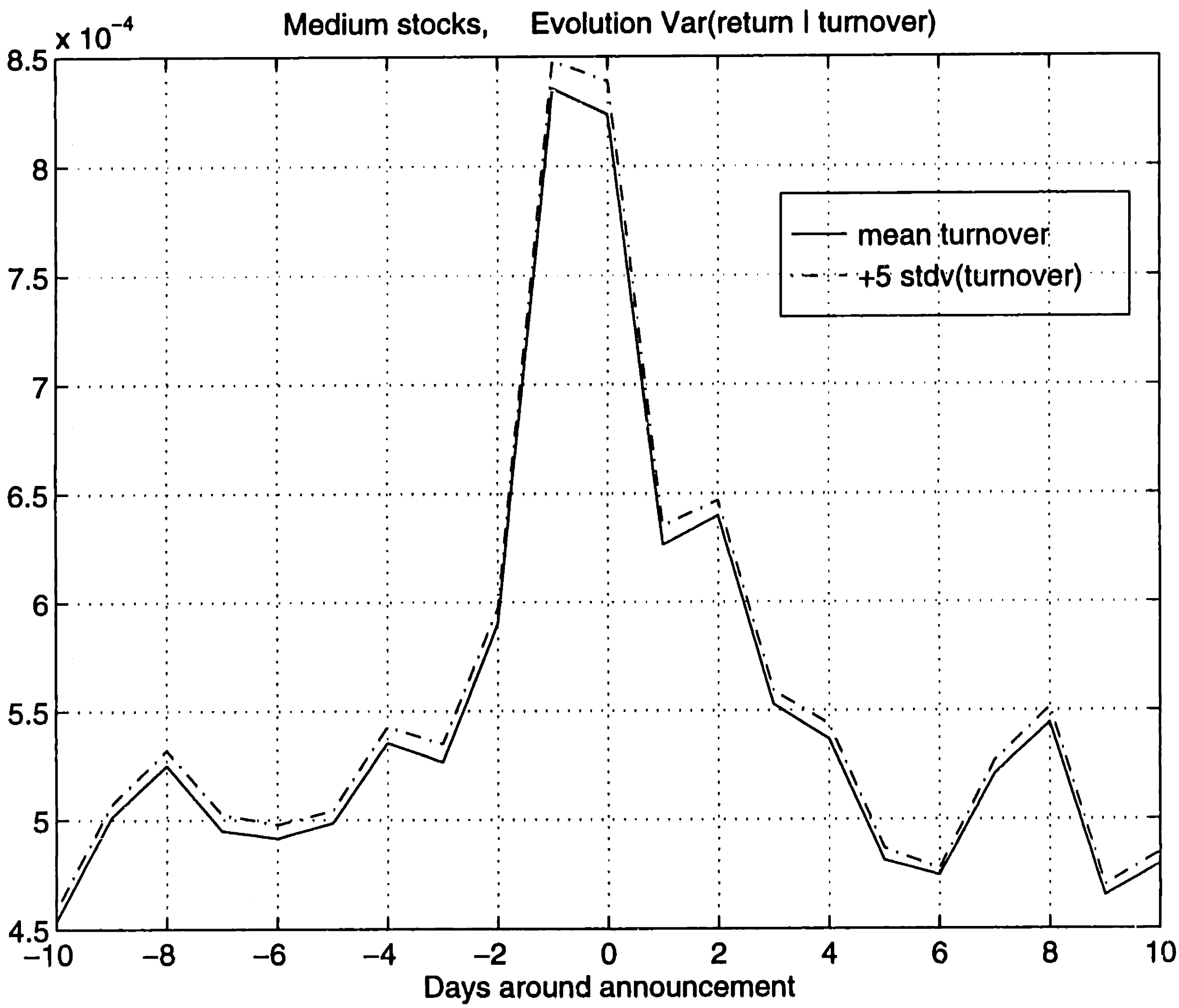

Figure 3-5: Medium Stocks: Variance of Return.

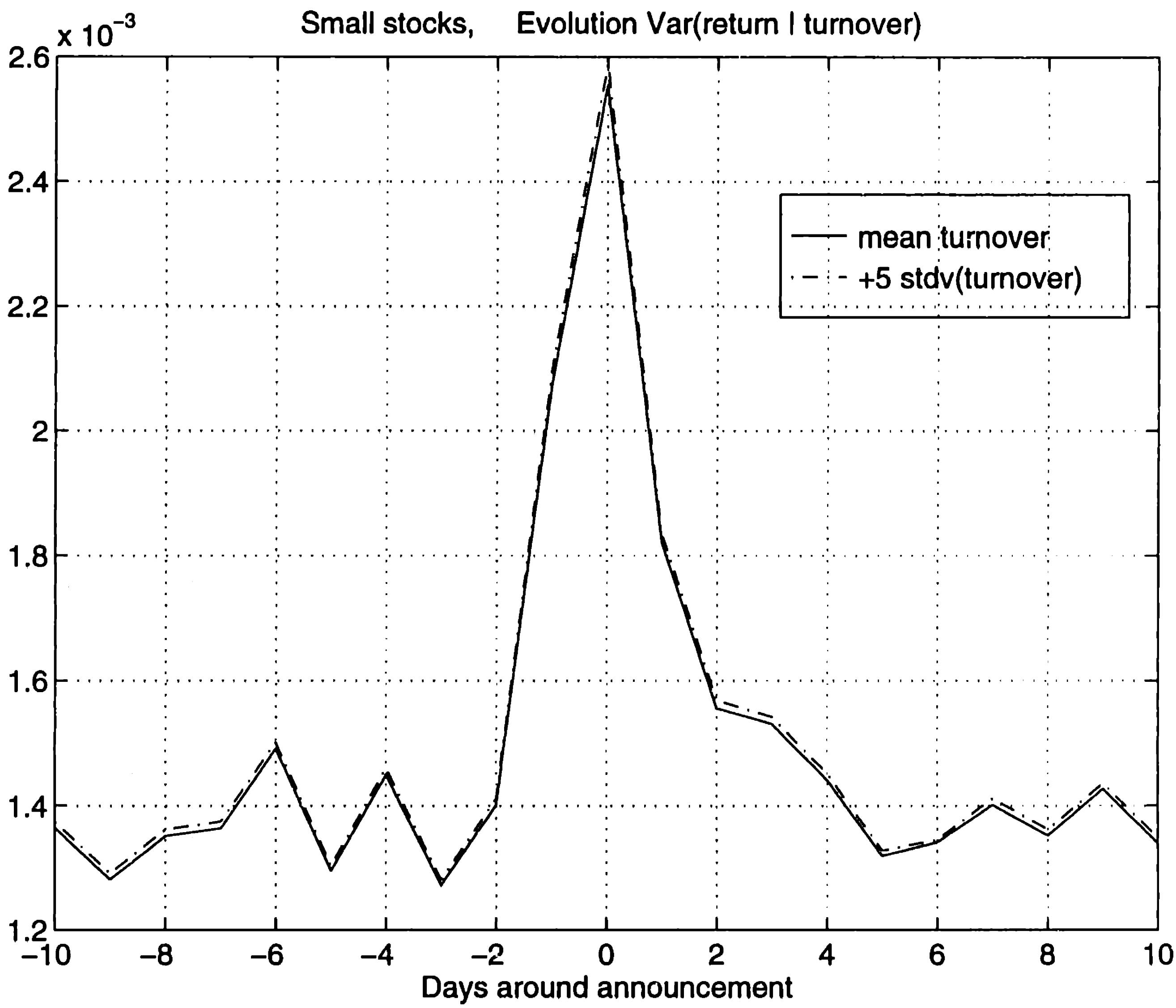

Figure 3-6: Small Stocks: Variance of Return.

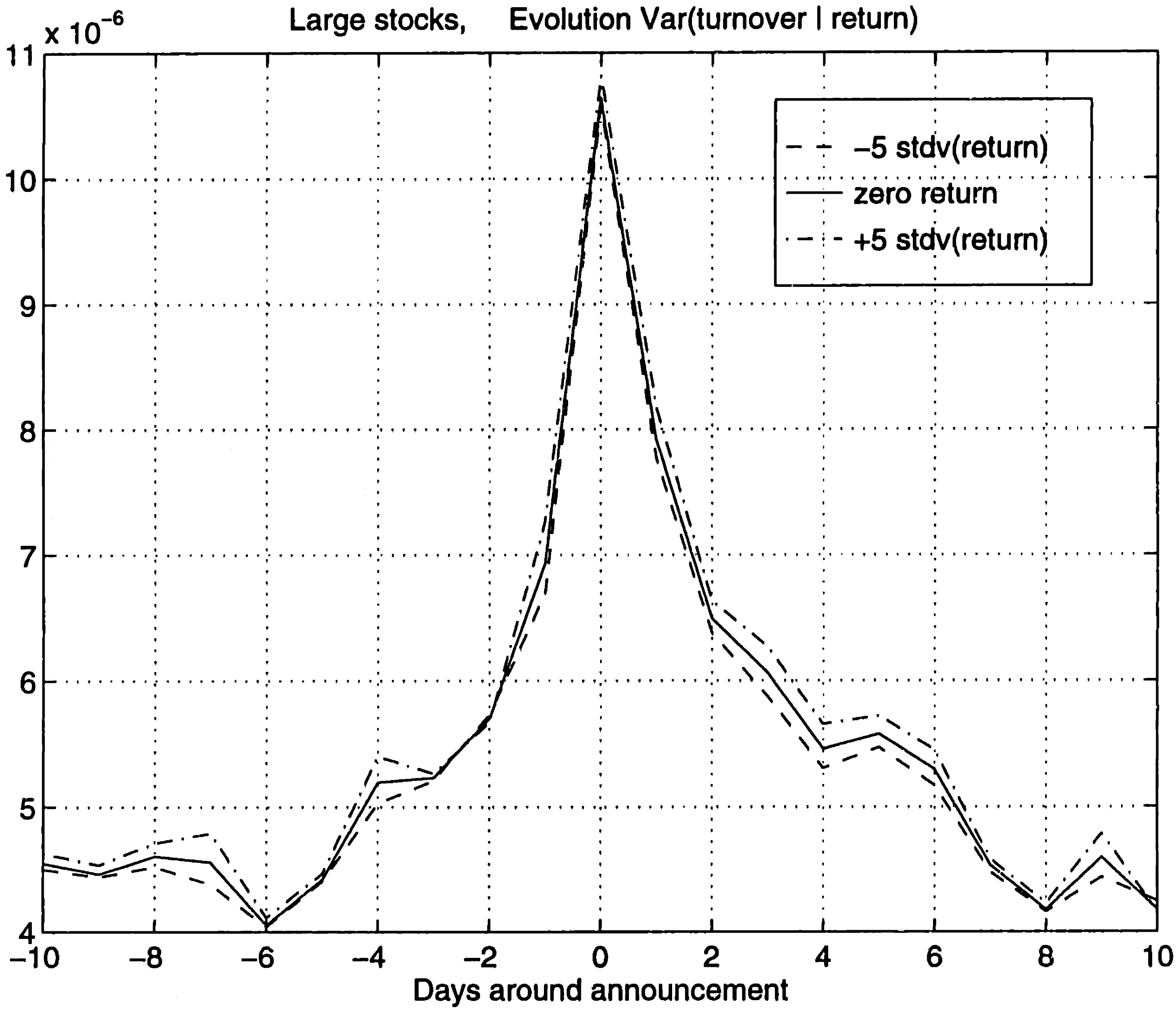

Figure 3-7: Large Stocks: Variance of Turnover.

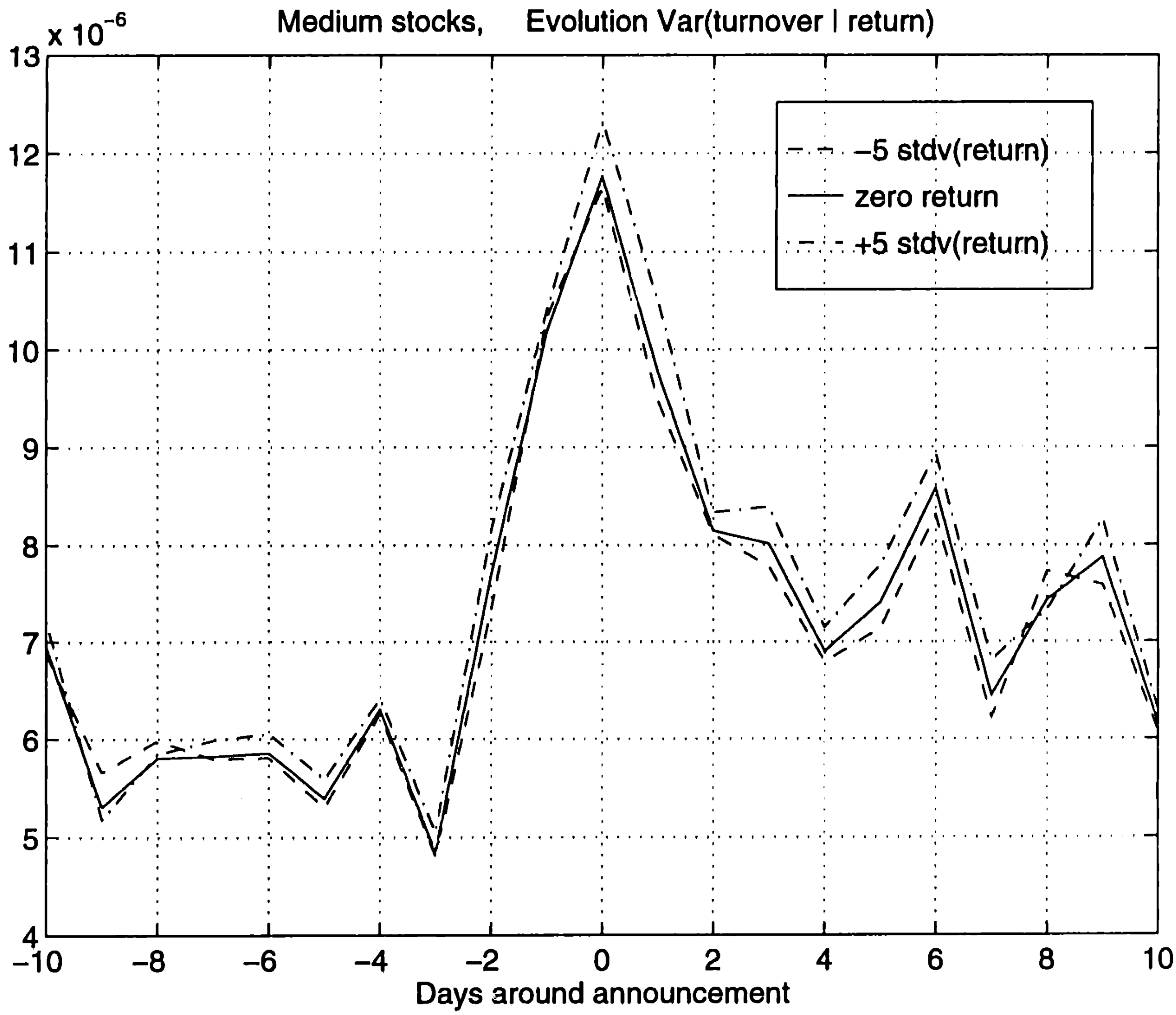

Figure 3-8: Medium stocks: Variance of Turnover.

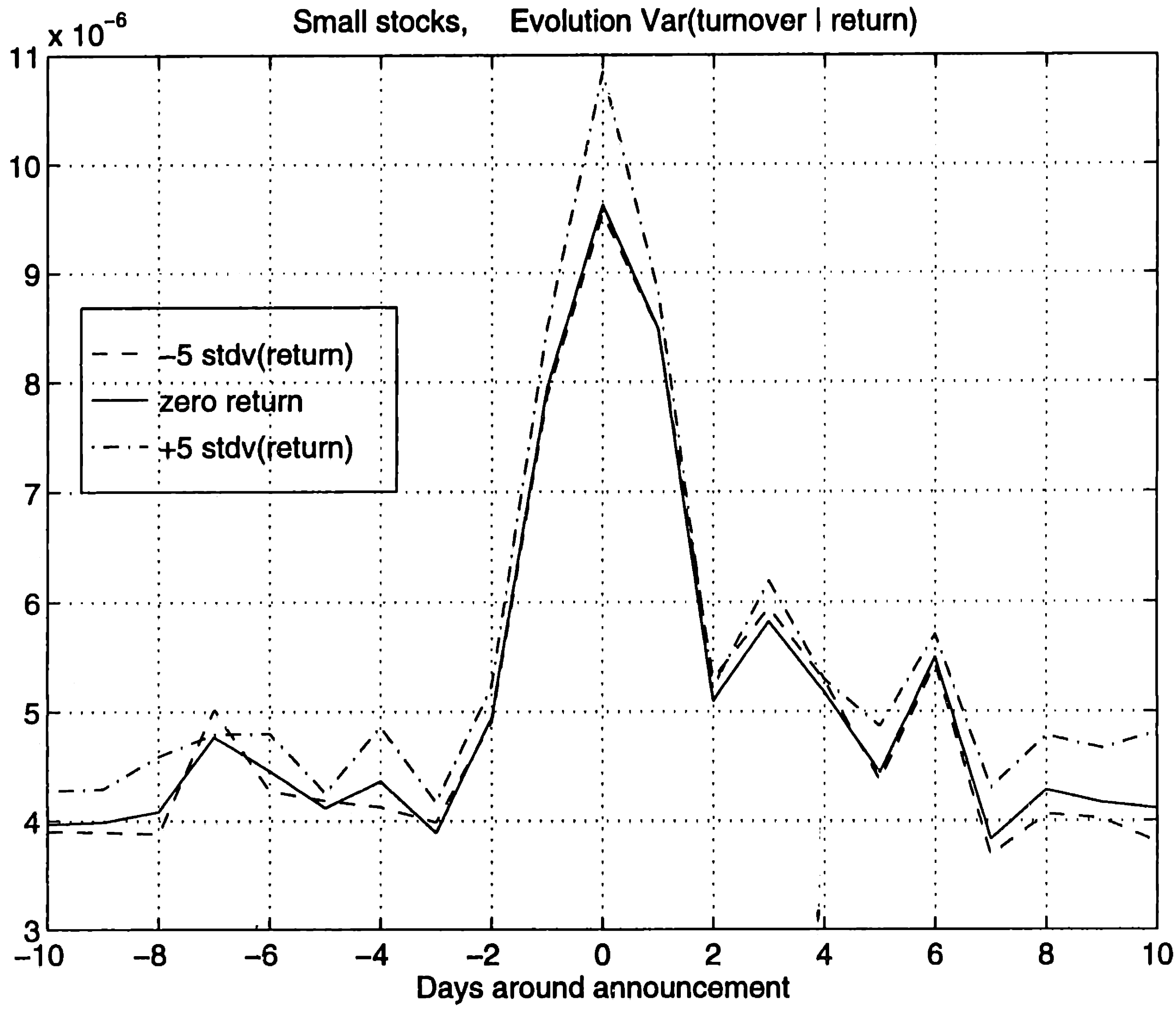

Figure 3-9: Small Stocks: Variance of Turnover.

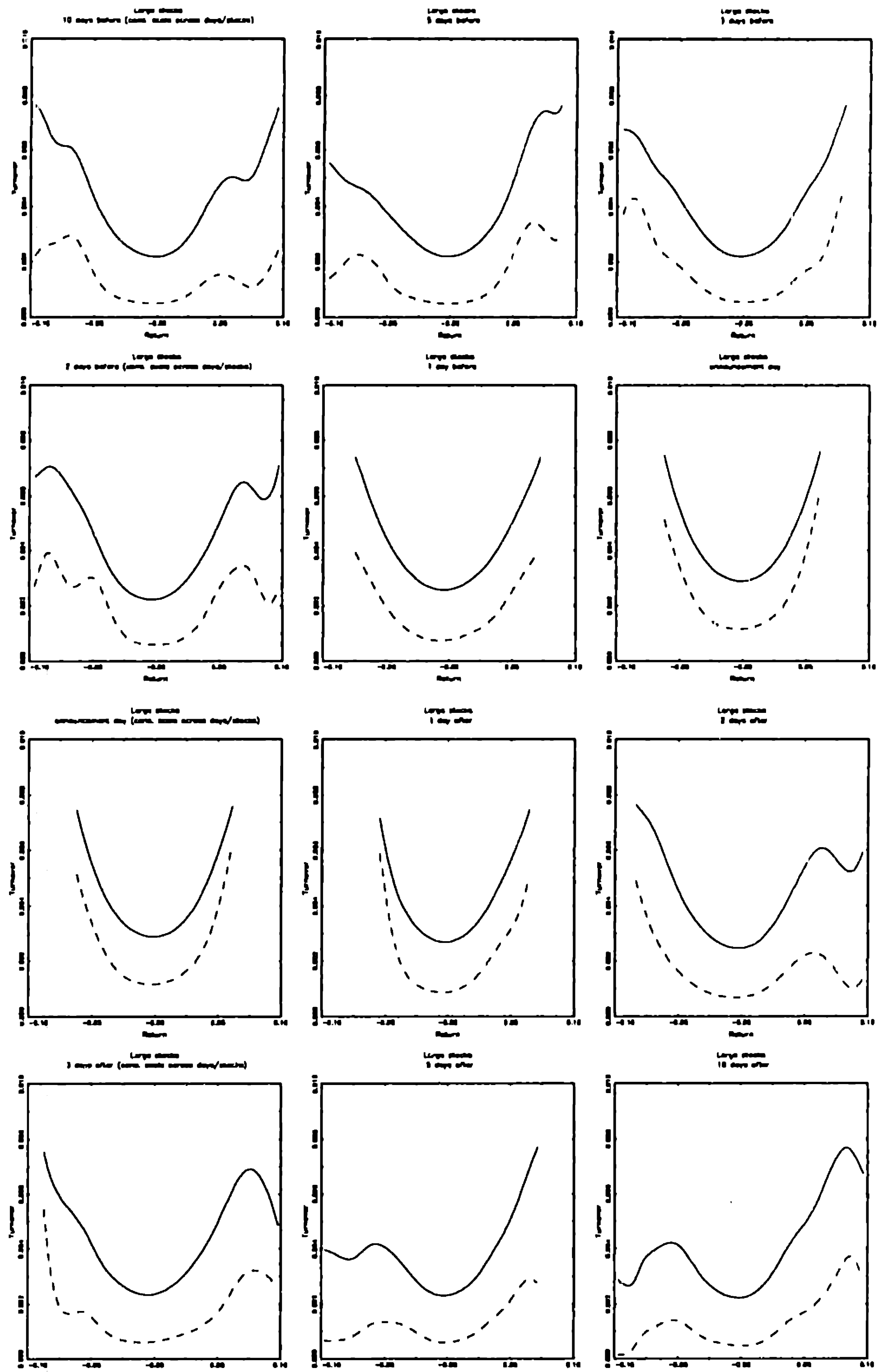

Figure 3-10: Large Stocks, $E(\text{turnover}|\text{return})$ Continuous Line and $Var(\text{turnover}|\text{return}) * 100$ Dashed Line.

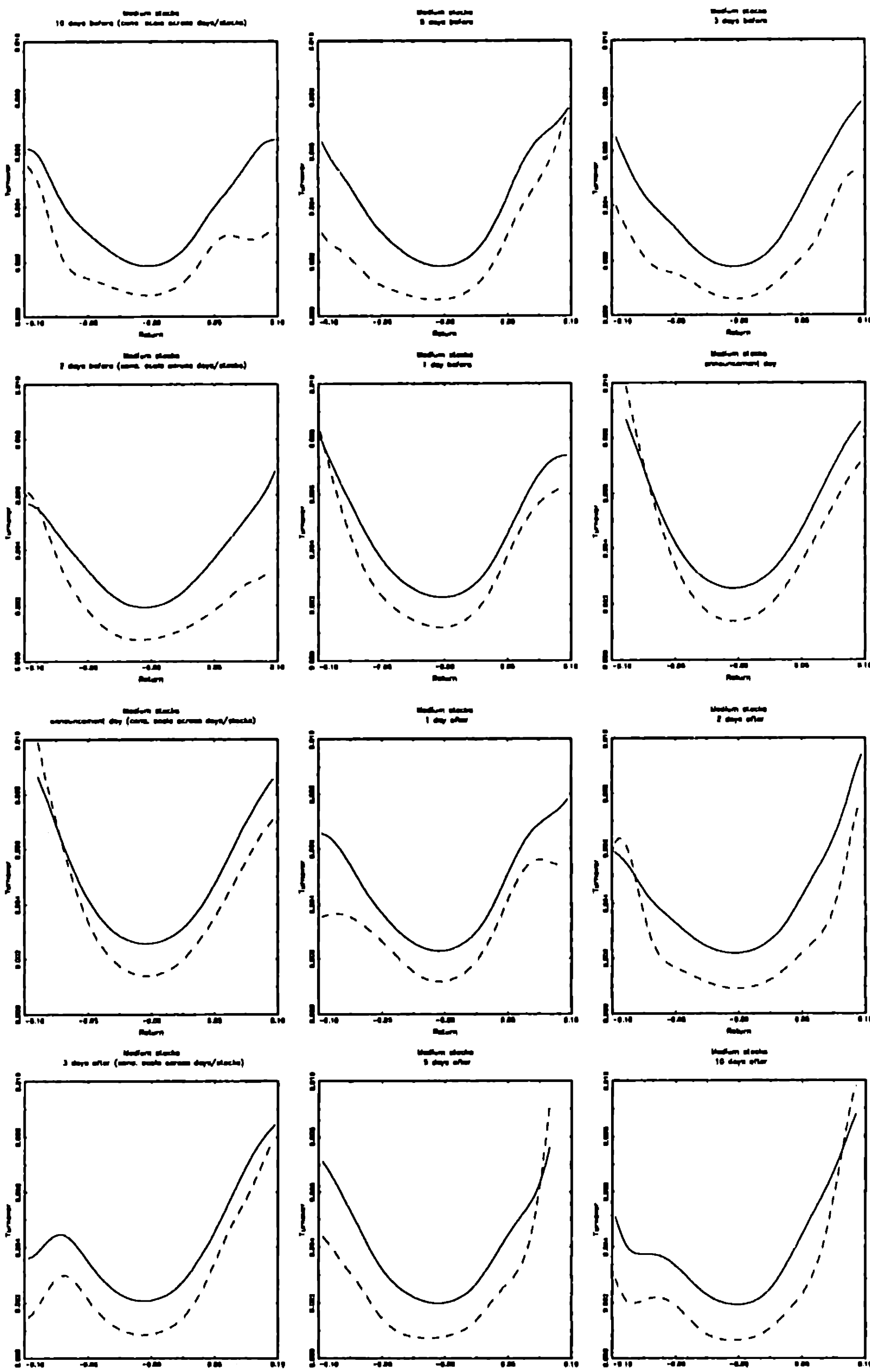

Figure 3-11: Medium Stocks, $E(\text{turnover}|\text{return})$ Continuous Line and $Var(\text{turnover}|\text{return}) * 100$ Dashed Line.

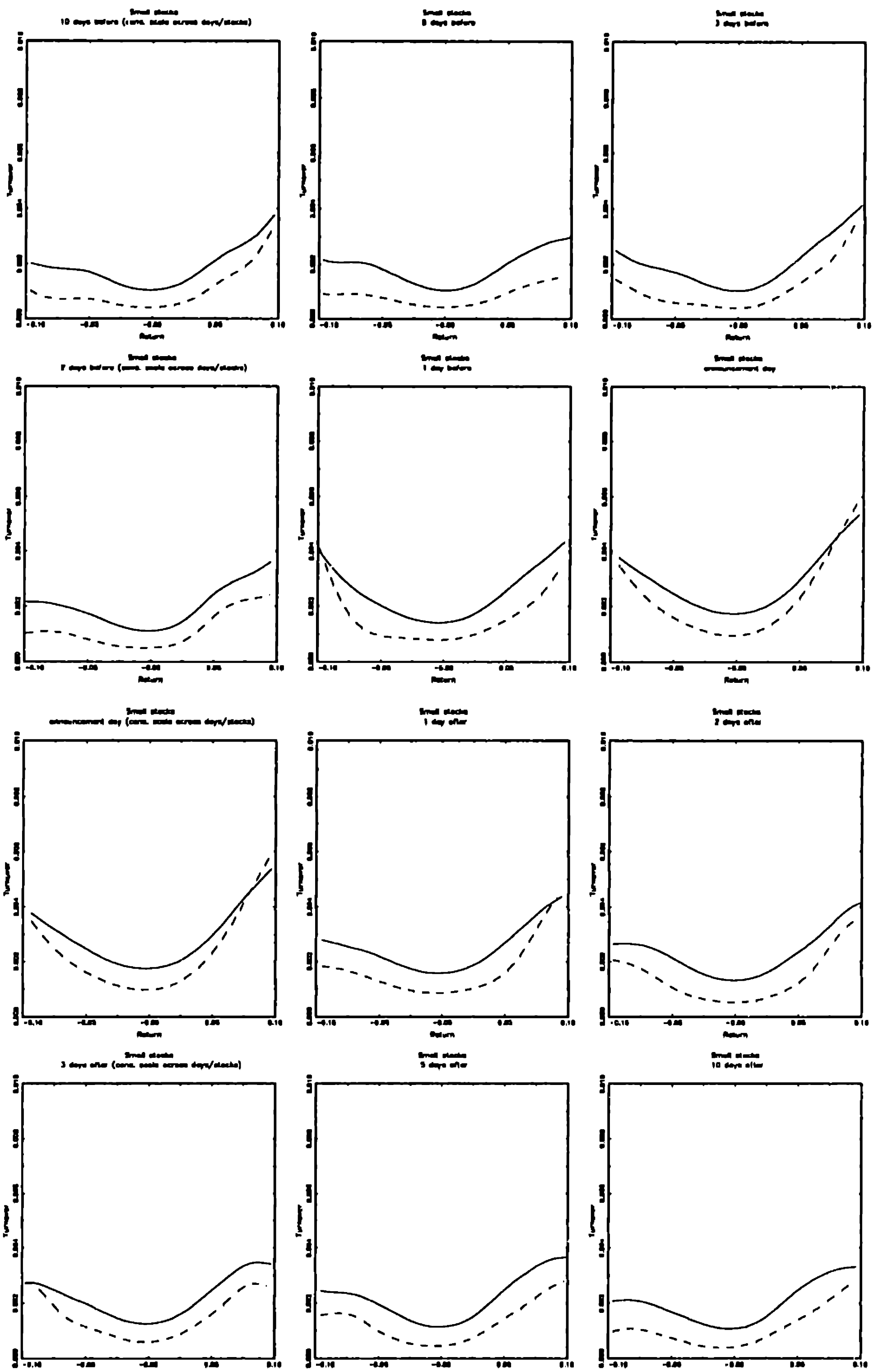

Figure 3-12: Small Stocks, $E(\text{turnover}|\text{return})$ Continuous Line and $Var(\text{turnover}|\text{return}) * 100$ Dashed Line.

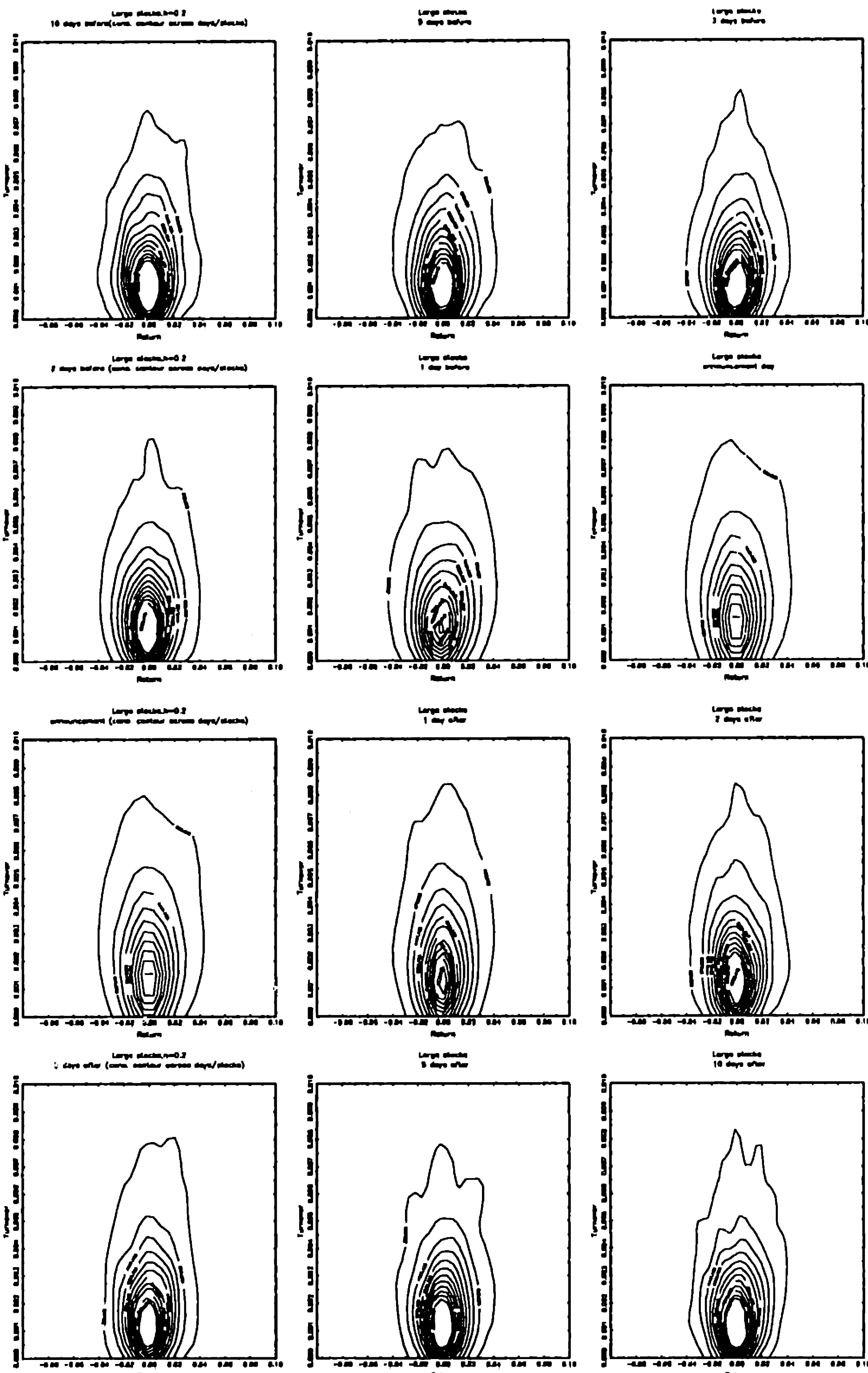

Figure 3-13: Large Stocks: Contour Plots.

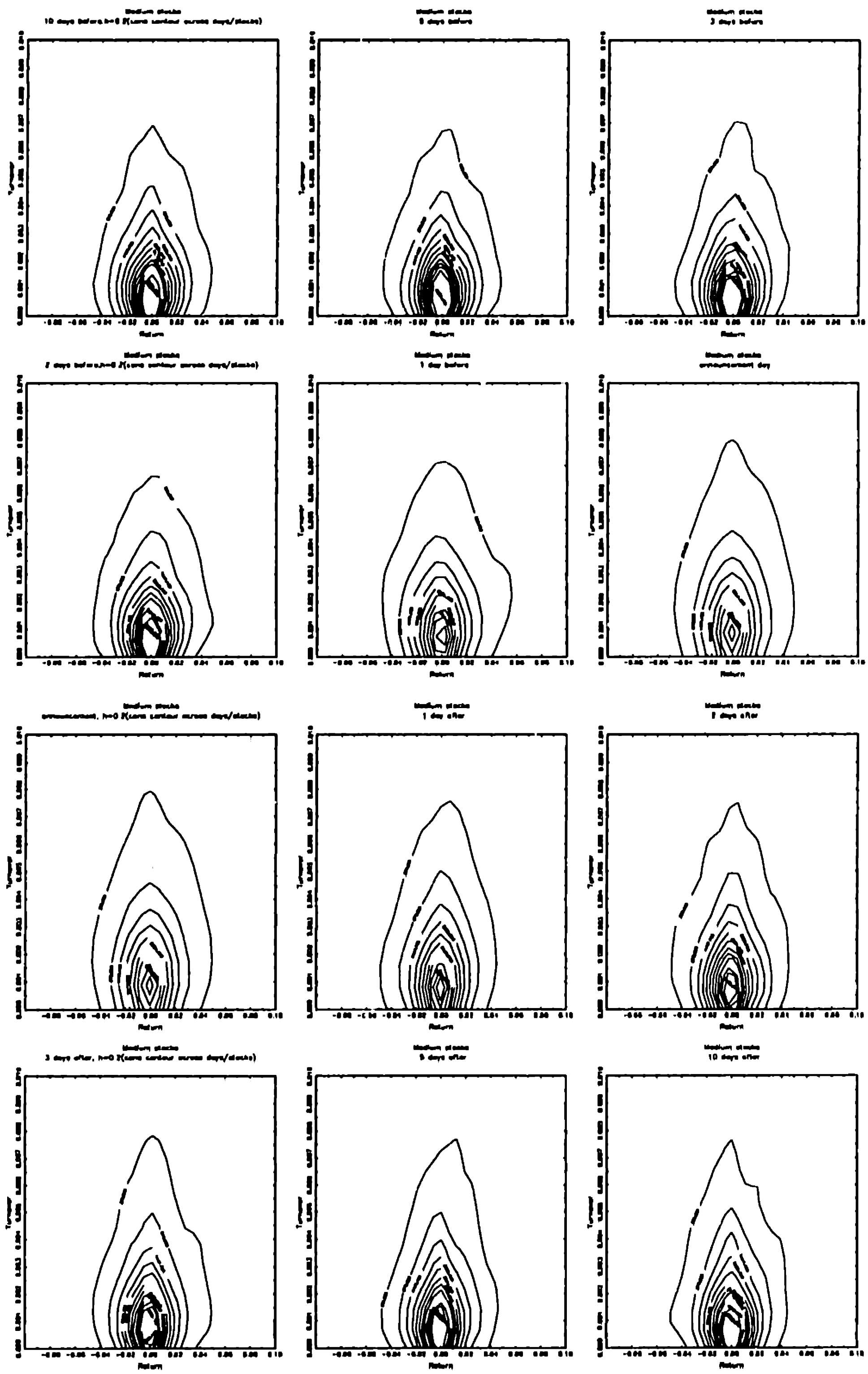

Figure 3-14: Medium Stocks: Contour Plots.

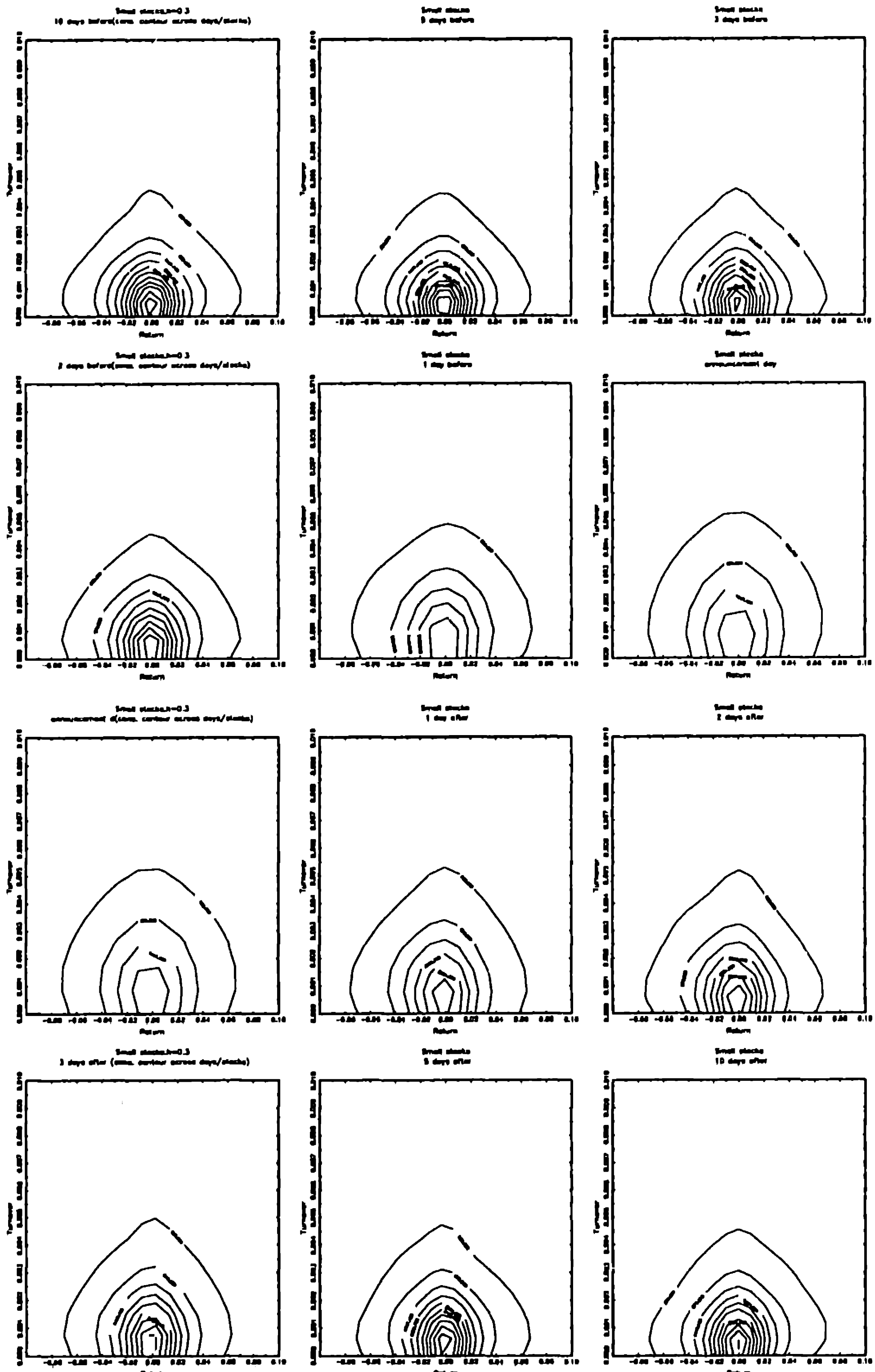

Figure 3-15: Small Stocks: Contour Plots.

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Chapter 4

Differentiating Between Volume and Return Information on Individual Stocks

CO-WRITTEN WITH LUDWIG CHINCARINI

4.1 Introduction

The accepted version of time varying risk premium and the increasing agreement about the non-linear relationships on the stock market, make it difficult to test for the general relationships among the variables in the market, such as volume and returns. The non-linearities present difficulties for testing all specifications of the market (LeBaron (1991)). Given these limitations, this article attempts to add more understanding to the issues without using any structural specification, and instead using what has been phrased *trading contrarian strategies.*

Many studies have found that *contrarian* strategies, that is strategies that sell winner stocks and buy loser stocks, can provide profits on average. There are two types of studies within this domain of research: those that consider short horizons (Lehmann

(1991), Lo and MacKinley (1991), and Conrad *et al.* (1994)), and those that consider longer horizons ((DeBondt and Thaler (1985)). Most of the studies related to trading strategies concern themselves with the stock market *overreaction* hypothesis (Lehmann (1991), Lo and MacKinley (1991), and DeBondt and Thaler (1985)). The common empirical hypothesis of these studies is that overreaction implies that price changes of securities must be negatively autocorrelated for some holding period.

Within the price-volume literature, the theoretical models of Blume *et al.* (1994) and Campbell *et al.* (1993) have examined the relationship between trading volume and returns. Blume *et al.* (1994) present a model in which volume has informational content by its own and is used by the investors in their decisions. In Campbell *et al.* (1993), volume is a variable of interest because of its correlation with other variables, but in itself is unimportant: investors do not learn from volume nor use it in any decision making process. One of the main implications of Campbell et al. (1993) is that "price changes accompanied by high volume will tend to be reversed. This will be less true of price changes on days with low volume."

Conrad *et al.* (1994) use a particular specification of trading strategies that combine the volume and price information and conclude that the theoretical work of Campbell *et al.* (1993) is supported empirically. Although the results of Conrad *et al.* (1994) are extremely interesting, we find that there is room for further investigation.

Though Blume *et al.* (1994) do not specify a particular trading rule, Campbell *et al.* (1994) do specify a particular relationship between volume and returns through their autocovariances. In this chapter, we will take the results of price reversal for high volume stocks that Campbell *et al.* (1993) have noticed and the conclusions about informational content of volume that Blume *et al.* (1994) have brought forth to test whether or not volume does contain information *per se* (that is apart from its identification function) in addition to that present in returns. We will also test whether the price reversals predicted by Campbell *et al.* (1994) do indeed exist.

We will develop four kinds of trading strategies for investment in order to test for these hypotheses. The first strategy, what we call *volume lead*, is implemented creating portfolios with volume weights given by the deviation of individual security volume from market volume. The name, *volume lead*, comes from the fact that trading volume is the variable that signals the action to take given a change in price and is supposed to "identify", as Campbell *et al.* point out, the reason for the price change. The second strategy, similar to the "return weights" in Conrad *et al.* (1994) uses volume as an indicator variable but the weights are entirely based on returns. That is the stocks are classified in the same way as in the volume lead strategy, but the weights are different. The comparison of the results between these two strategies will give us important insights into the informational content of the trading volume. The third and fourth strategies combine both the return and volume information, keeping the same portfolio division. One can think in terms of overreaction or contrarian strategies when examining either strategy, however as we will see, of the four trading portfolios, only two of them, those related to high volume, can be considered to be contrarian, the other two are not. The reason for this classification is be able to make straightforward comparisons with the theory of Campbell *et al.* (1993). As a benchmark, we will also give the results obtained if a contrarian strategy for all portfolios is followed. The variable of study will be the profit of portfolios of securities formed following the dynamics imposed by each strategy.

One important point in all of the studies that deal with trading strategies is the impossibility of accounting for the risk of the position in each period. Because we focus only on the expected profits of these trading strategies and not on risk, this study, as others in the past, should be considered as a convenient tool for exploring the covariance properties of the variables of concern. Therefore, the results have theoretical implications only to the extent that they provide restrictions on economic models that must be consistent with the empirical results.

The first step is to specify some strategies for agents to follow based on a theoretical framework. This will allow us to avoid problems with the structural specification of the non-linear relation, though in fact the strategies are also non-linear. Second, to test the strategies we will use portfolios of individual securities, portfolios that can be constructed either by firm size, by volume of trade, or a combination of both. With this agenda we hope to shed some light, not only on the general relation between price and volume, but also to the differences and/or similarities when more specific characteristics about the stocks are considered.

One point we find important, but lacking in the work of Conrad *et al.*, is some measure of the aggregate portfolio. We think that the weights should consider the possible interrelations between returns and volume among securities due to the way agents choose and rebalance portfolios in the market. Thus, while the inclusion of an aggregate measure can cause cross-correlation effects and is thus difficult to interpret, we think that it can also add some valuable information.

The main results of the chapter are as follows. Trading volume has important informational content *per se* apart from its identification role and is different from the informational content of returns. The profits from the strategies that consider only volume as the weighting variable have the same qualitative but different quantitative results as those in which the weights are based solely on returns or a combination of returns and volume. Second, as Campbell *et al.* (1993) point out, we find price reversal for those stocks that experience a decline in price and have high trading volume with respect to the market. We cannot conclude anything about stocks that have a price increase and have higher than market volume. Finally, contrary to what one would expect, stocks with low volume also experience price reversal, independently of the direction of the change in price. These results are robust to the classification of stocks by size, particularly for smaller size stocks. From the results of following contrarian strategies, we can assert the dominance of this action to the one executed before. We can also state that by using volume and price information, the investors can significantly do better than using only volume and slightly better than using only return as is pointed out by Blume *et al.* (1994).

Though our work is not directly comparable to the Conrad *et al.* (1994) paper, where possible to make a comparison, we have found that our results are only different for those stocks which experience a decline in price and have a low trading volume with respect to the market. We think that this difference comes mainly from our definition of trading volume which is different that the one used by Conrad *et al.* (1994) and will be explained in the next section.

The rest of this chapter is organized as follows. Section 4.2 provides the basic setup of the hypothesis to be tested and a description of the previous research. Section 4.3 illustrates the trading strategies that are used in the analysis. Section 4.4 describes the data sources, the sample selection, and discusses the results of this article. Section 4.5 concludes the article.

4.2 Motivation for the Analysis

The theoretical literature that studies asset prices and trading volume can be divided into two branches: rational expectations asset pricing models and models based on differences of opinion. Rational expectation models are motivated by differences in information. They focus on the differences between privately informed traders, uninformed traders, and noise traders (Grossman and Stiglitz (1976, 1980), Wang (1992), He and Wang (1993), Pfleiderer (1984), Kyle (1985), and Blume *et al.* (1994)[1]). The literature concerning differences of opinion generally bases itself on different reactions from traders to stock announcements (Harris and Raviv (1993), Kandel and Pearson (1992), and Varian (1985, 1989)).

In recent articles, Blume *et al.* (1994) and Campbell *et al.* (1993) have examined the theoretical relationships between trading volume and returns. Blume et al. present an equilibrium model in which "volume provides information on information

[1]In this model, the agents have myopic behavior, because of the relevation of the information each period.

quality that cannot be deduced from the price statistics"; agents include the volume in their learning process, and the model suggests that there is a relationship between lagged volume and current returns on individual securities.

Campbell *et al.* explore the relationship between volume and returns by modelling the interactions between liquidity investors and risk-averse expected maximizers (that act as market makers). The market makers have to be compensated for satisfying the demands of liquidity traders in such a way, that an actual change in price, because of a selling pressure by liquidity traders, should be compensated by a change in the expected return. Volume information can help to distinguish between price movements which are due to the release of public information and those which reflect changes in expected returns. One of the main implications of their paper is that "... price changes accompanied by high volume will tend to be reversed; this will be less true of price changes on days with low volume...".

Following some of the theoretical articles on volume trading and returns, empirical research has attempted to verify the relationships between market volume and returns. Within this field, two directions have been taken. One set of studies has focused on the effects of new stock announcements, typically earnings announcements, on price and trading volume (Karpoff (1987), Morse (1980), Stickel and Verrechia (1992), and Kandel and Pearson 1993)). Another set of studies has focused on some structural specification, generally non-linear in nature (Campbell *et al.* (1993), LeBaron (1991), Gallan et al. (1992), Conrad *et al.* (1994), and Llorente (1995)). Most of these articles work with aggregate measures of price (return) and volume. In working with individual stocks, Llorente (1995) finds that volume (individual, as well as market) can add some information to the autocorrelations of individual stock returns in forecasting returns. The importance of volume is greater for small stocks. Conrad *et al.* (1994), using a variant of Lehmann's (1990) contrarian trading strategy, find evidence of a relationship between trading activity and subsequent autocovariances for individual weekly stock returns. "High-transaction securities experience price reversals, while low transaction securities have positive autocorrelated returns."

In this chapter we are going to test for the informational content of lagged volume and price as suggested by Blume *et al.* (1994) by developing some trading rules based on the results of Campbell *et al.* (1993). As a by-product of the design of the strategies, we will be able to test for the different behavior in prices corresponding to volume as postulated by Campbell et al. (1993).

We will use a variant of the Lehmann (1990) and Lo and MacKinlay (1990) contrarian portfolio strategies to measure the strength of the volume/return relationship. In a given period of time, t, we will classify the stocks into two portfolios according to their return in $t-k$ (positive or negative) and conditional on this we further divide them by volume (high or low with respect to the market) at time $t-k$ periods prior to the current period. Thus, we will have four portfolios. Depending on the classification, we will either short sell or buy the stocks in each portfolio by a dollar amount which will be specified in section 4.3. These weights will be determined by volume, return, or a combination of volume and return. For each portfolio, the weights are normalized so that they sum to one. This enables the formation of combined portfolios that are zero investment.

The method proposed has several important advantages over previous studies. To begin with, we measure profits and can provide statistics and economic information about the relationship between volume and return. Second, the profits from the first proposed strategy are directly related to the covariances between lagged volume and return, which are important in Blume *et al.* Third, the comparison of the profits from this strategy and the other two will allow us to address the information contained in the trading volume more accurately. Finally, these strategies are all examples of technical analysis.[2]

There are several important characteristics that differentiate our work from Con-

[2]Technical analysis is the study of volume and price information with the belief that it can provide information about underlying fundamentals not present in the price statistic alone.

rad *et al.* (1994). First, our method to test for the importance of trading volume is completely different. Trading volume enters in all of their weight schemes as a modification of the information already transmitted by the returns. The profits from our *volume lead* strategy are directly related to the covariance between lagged volume and returns. This will avoid any influence of the bid-ask spread on the autocorrelations of returns. Second, using turnover as a variable for trading activity instead of the number of transactions or dollar-value volume we avoid differences across firms because of the different number of shares outstanding, prices, and any distortions due to block transactions. Moreover, as Cready and Mynatt (1991) point out, turnover can better reflect the informational content of the trade than the number of transactions. Lastly, we define high or low volume as the difference between individual turnover and market turnover. In this way, we consider individual stocks within the market and the idea of diversification when forming portfolios. This might produce cross effects among various stocks, which will add complication to the interpretation of the results, but we feel that it is important to consider the presence of the market.

4.3 Trading Strategies

4.3.1 A Volume Lead Strategy

The name for this strategy comes from the role that trading volume plays in it. Given a change in price, thus a high or low return stock, whether to buy or sell and how much to buy or sell will depend on the volume variable. The basic idea, following Campbell *et al.* (1993), is that price changes accompanied by high volume of a security in period $t-k$, indicate a high probability of price reversal in the near future, whereas, this is not true for price changes accompanied by low volume.

The difficult part in this set up is to define over what horizon will there be a reversal or when is the optimal timing between the pressure in the volume and the expected return. It could be argued that they are simultaneous, though the results of Campbell, *et al.* (1993), Conrad et al. (1994), and Llorente (1995) show that (as Stickel and Verrechia (1992) have argued) in a context of rational expectations "it takes at least one period for investors to compile and assimilate information about volume". We will assume that it takes at least one period for the market to incorporate information about volume, so that the change of direction in the change in price will occur at least one period later, and thus the strategy will be defined to follow this rule.[3]

The specification of the strategy is as follows: Consider a given set of N securities over T time periods. At the beginning of period t, divide the securities into two groups, those with a positive return in period $t-k$ and those with a negative return in period $t-k$.[4] Within the positive return or *winner* portfolio, short sell $u_{it}^{W,H}(k)$ dollars of the high volume securities and go long $u_{it}^{W,L}(k)$ dollars of low volume stocks. That is, short sell only those securities with a higher than market volume of trade in period $t-k$ and go long those securities with a lower trade volume than the market in period $t-k$. One must pursue the opposite (i.e. short sell low volume stocks and buy high volume stocks) for negative return securities. The intuition for these strategies comes from Campbell *et al.* (1993). They state that high volume securities will experience price reversal, but low volume securities will not. Therefore, as mentioned above, the trading strategies behave only in contrarian fashion for those securities that have a higher than market volume due to the expected negative autocorrelation. This will create four different portfolios of stocks. In each of these portfolios we will invest one dollar ($\sum u_{it}(k) = 1$).[5] The strategies are summarized below:

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[3] In this chapter, we will also study the behavior of the strategies for different lag periods.

[4] The value of k will be a constant that is determined *ex ante*, in our study k is equal to 1,2,4,and 26 weeks.

[5] It turns out, that in two portfolios, we will short sell one dollar and in two of them we will invest one dollar, making the overall strategy a zero-investment strategy. The reader should also realize that we can scale the one dollar by any positive amount.

$$R_{it-k} > 0 \Rightarrow \begin{cases} V_{it-k} > V_{mt-k} \Rightarrow & u_{it}^{W,H}(k) = -\frac{(V_{it-k}-V_{mt-k})}{\sum_{i=1}^{N_{WH}}(V_{it-k}-V_{mt-k})} \\ V_{it-k} \leq V_{mt-k} \Rightarrow & u_{it}^{W,L}(k) = \frac{(V_{it-k}-V_{mt-k})}{\sum_{i=1}^{N_{WL}}(V_{it-k}-V_{mt-k})}, \end{cases} \tag{4.1}$$

$$R_{it-k} \leq 0 \Rightarrow \begin{cases} V_{it-k} > V_{mt-k} \Rightarrow & u_{it}^{L,H}(k) = \frac{(V_{it-k}-V_{mt-k})}{\sum_{i=1}^{N_{LH}}(V_{it-k}-V_{mt-k})} \\ V_{it-k} \leq V_{mt-k} \Rightarrow & u_{it}^{L,L}(k) = -\frac{(V_{it-k}-V_{mt-k})}{\sum_{i=1}^{N_{LL}}(V_{it-k}-V_{mt-k})}, \end{cases} \tag{4.2}$$

where R_{it-k} is the return for each security at time $t-k$, V_{it-k} is the volume traded of security i in period $t-k$ and V_{mt-k} is the average volume traded in all securities in period $t-k$; that is, $V_{mt-k} = \frac{1}{N}\sum_{i=1}^{N} V_{it-k}$. In this article we shall define volume as the ratio of the number of shares traded to the number of shares outstanding (referred to as turnover). This will make V_{it-k} bounded on the interval $[0, 1]$. Consequently, u_{ipt} will be bounded on the interval $[-1, 1]$.

These strategies give us a combination of four portfolios. Two of these portfolios will be sold short and two will be bought. The profits from the combined strategies at time t will be given by:

$$\begin{aligned} \pi_t(k) &= \sum_{i=1}^{N_{WH}} u_{it}^{W,H}(k)R_{it}^{WH} + \sum_{i=1}^{N_{WL}} u_{it}^{W,L}(k)R_{it}^{WL} + \\ & \sum_{i=1}^{N_{LH}} u_{it}^{L,H}(k)R_{it}^{LH} + \sum_{i=1}^{N_{LL}} u_{it}^{L,L}(k)R_{it}^{LL}. \end{aligned} \tag{4.3}$$

We shall now analyze the profits for any generic portfolio. To begin with, we define N_p as the number of securities included in the portfolio of a certain strategy at any time t, where $N_p \subset N$. The weights in this generic portfolio are:

$$u_{it}(k) = \frac{(V_{it-k} - V_{mt-k})}{\sum_{i=1}^{N_p}(V_{it-k} - V_{mt-k})}, \tag{4.4}$$

where $V_{mt-k} = \frac{1}{N}\sum_{i=1}^{N} V_{it-k}$. The normalization factor assures that we will invest one dollar in the portfolio ($\sum_{i=1}^{N_p} u_{it}(k) = 1$). The profits in period t are:

$$\pi_t(k) = \sum_{i=1}^{N_p} \frac{(V_{it-k} - V_{mt-k})}{\sum_{i=1}^{N_p}(V_{it-k} - V_{mt-k})} R_{it}. \tag{4.5}$$

To make the notation simpler, define $\gamma_{it-k} = \frac{V_{it-k}}{\sum_{i=1}^{N_p}(V_{it-k}-V_{mt-k})}$ and $\gamma_{mt-k} = \frac{V_{mt-k}}{\sum_{i=1}^{N_p}(V_{it-k}-V_{mt-k})}$.

The mean profits over T periods of this k period ahead portfolio strategy will be:[6]

$$\bar{\pi}_t(k) = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k} - \gamma_{mt-k})R_{it} \tag{4.6}$$

$$= -\frac{1}{T}\sum_{t=1}^{T} N_p(\gamma_{t-k}^p - \bar{\gamma}^p)(R_t^p - \bar{R}^p) + \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k} - \bar{\gamma}^p)(R_{it} - \bar{R}^p) + \frac{1}{T}\sum_{t=1}^{T} R_t^p \sum_{i=1}^{N_p}(\gamma_{it-k} - \gamma_{mt-k}), \tag{4.7}$$

where $\gamma_{t-k}^p = \frac{1}{N_p}\sum_{i=1}^{N_p}\gamma_{it-k}$, $R_t^p = \frac{1}{N_p}\sum_{i=1}^{N_p} R_{it}$, $\bar{\gamma}^p = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_p}\sum_{i=1}^{N_p}\gamma_{it-k}$, and $\bar{R}^p = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_p}\sum_{i=1}^{N_p} R_{it}$.[7]

Thus, average portfolio profits depend on the cross-covariances of the means of an equally weighted portfolio, the covariances between the volume and the return of the individual securities in the portfolio, and the arithmetic mean of the returns of the securities in the portfolio multiplied by the sum of all the weights. Therefore, the consideration of a market measure for trading volume will not produce direct important cross-sectional effects, besides those among securities in the same portfolio.

[6] The proof is included in the appendix for completeness.

[7] N_p depends on time the way our strategies have been defined, thus we cannot remove it from the summation over time.

4.3.2 The Volume Lead Strategy with Return Only Based Weights

This strategy is very similar in spirit to the one above. The only modification is that the weights from above are scaled *only* by the actual returns in period $t-k$. Following the results of Lo and MacKinlay (1990), we have avoided using any measure of market return to prevent the cross-autocovariances among stocks to influence our conclusions. For the market volume, this is not a major problem as we explained above. This modification will allow us to access the information contained in our measure of volume. The strategies are summarized below:

$$R_{it-k} > 0 \Rightarrow \begin{cases} V_{it-k} > V_{mt-k} \Rightarrow & u_{it}^{W,H} = -\frac{R_{it-k}}{\sum_{i=1}^{N_{WH}} R_{it-k}} \\ V_{it-k} \leq V_{mt-k} \Rightarrow & u_{it}^{W,L} = \frac{R_{it-k}}{\sum_{i=1}^{N_{WL}} R_{it-k}}, \end{cases} \tag{4.8}$$

$$R_{it-k} \leq 0 \Rightarrow \begin{cases} V_{it-k} > V_{mt-k} \Rightarrow & u_{it}^{L,H} = \frac{R_{it-k}}{\sum_{i=1}^{N_{LH}} R_{it-k}} \\ V_{it-k} \leq V_{mt-k} \Rightarrow & u_{it}^{L,L} = -\frac{R_{it-k}}{\sum_{i=1}^{N_{LL}} R_{it-k}}, \end{cases} \tag{4.9}$$

where R_{it-k} is the return for each security at time $t-k$, V_{it-k} is the volume traded of security i in period $t-k$ and V_{mt-k} is the average volume traded in all securities in period $t-k$; that is, $V_{mt-k} = \frac{1}{N}\sum_{i=1}^{N} V_{it-k}$.

4.3.3 The Volume Lead Strategy with Volume and Return Based Weights

Once the difference between the covariances of lagged volume and lagged return to the present returns is known independently, the next logical step is to evaluate these covariances considering all three variables together, that is lagged volume, lagged returns, and current returns. We will deal with this by proposing two alternative weighting schemes. The first weight, called VLR1, is a combination of lagged volume and lagged returns. The second weight, called VLR2, follows closely to the weights proposed by Conrad *et al.* (1994). In VLR2, volume only alters the autocovariance between returns and lagged returns. The main difference between VLR1 and VLR2 is the way in which the information compounded in volume enters in the autocorrelation in returns.

The strategy with more direct influence of volume information (VLR1) is given by:

$$R_{it-k} > 0 \Rightarrow \begin{cases} V_{it-k} > V_{mt-k} \Rightarrow & u_{it}^{W,H} = -\frac{(V_{it-k}-V_{mt-k})R_{it-k}}{\sum_{i=1}^{N_{WH}}(V_{it-k}-V_{mt-k})R_{it-k}} \\ V_{it-k} \leq V_{mt-k} \Rightarrow & u_{it}^{W,L} = \frac{(V_{it-k}-V_{mt-k})R_{it-k}}{\sum_{i=1}^{N_{WL}}(V_{it-k}-V_{mt-k})R_{it-k}}, \end{cases} \tag{4.10}$$

$$R_{it-k} \leq 0 \Rightarrow \begin{cases} V_{it-k} > V_{mt-k} \Rightarrow & u_{it}^{L,H} = \frac{(V_{it-k}-V_{mt-k})R_{it-k}}{\sum_{i=1}^{N_{LH}}(V_{it-k}-V_{mt-k})R_{it-k}} \\ V_{it-k} \leq V_{mt-k} \Rightarrow & u_{it}^{L,L} = -\frac{(V_{it-k}-V_{mt-k})R_{it-k}}{\sum_{i=1}^{N_{LL}}(V_{it-k}-V_{mt-k})R_{it-k}}, \end{cases} \tag{4.11}$$

where R_{it-k} is the return for each security at time $t-k$, V_{it-k} is the volume traded of security i in period $t-k$ and V_{mt-k} is the average volume traded in all securities in period $t-k$; that is, $V_{mt-k} = \frac{1}{N}\sum_{i=1}^{N} V_{it-k}$.

The strategy in which volume only modifies the autocovariance between lagged return and current return (VLR2) is given by:

$$R_{it-k} > 0 \Rightarrow \begin{cases} V_{it-k} > V_{mt-k} \Rightarrow & u_{it}^{W,H} = -\frac{(1+[V_{it-k}-V_{mt-k}])R_{it-k}}{\sum_{i=1}^{N_{WH}}(1+[V_{it-k}-V_{mt-k}])R_{it-k}} \\ V_{it-k} \leq V_{mt-k} \Rightarrow & u_{it}^{W,L} = \frac{(1+[V_{it-k}-V_{mt-k}])R_{it-k}}{\sum_{i=1}^{N_{WL}}(1+[V_{it-k}-V_{mt-k}])R_{it-k}}, \end{cases} \tag{4.12}$$

$$R_{it-k} \leq 0 \Rightarrow \begin{cases} V_{it-k} > V_{mt-k} \Rightarrow & u_{it}^{L,H} = \frac{(1+[V_{it-k}-V_{mt-k}])R_{it-k}}{\sum_{i=1}^{N_{LH}}(1+[V_{it-k}-V_{mt-k}])R_{it-k}} \\ V_{it-k} \leq V_{mt-k} \Rightarrow & u_{it}^{L,L} = -\frac{(1+[V_{it-k}-V_{mt-k}])R_{it-k}}{\sum_{i=1}^{N_{LL}}(1+[V_{it-k}-V_{mt-k}])R_{it-k}}, \end{cases} \tag{4.13}$$

where R_{it-k} is the return for each security at time $t-k$, V_{it-k} is the volume traded of security i in period $t-k$ and V_{mt-k} is the average volume traded in all securities in period $t-k$; that is, $V_{mt-k} = \frac{1}{N}\sum_{i=1}^{N} V_{it-k}$.

The second strategy follows more closely the spirit of the structural specification of Campbell *et al.* (1993). The autocovariance in returns is always the predominant factor in this strategy. Given the bounds of the volume measure discussed above, these weights only increase or decrease the weighting based on return information.

4.4 Empirical Analysis

To determine whether volume has informational content and whether it has different informational content than returns, we examine a sequence of trading rules. First, we examine profits from a portfolio strategy with weights based on volume information only. Next, we examine the differences in profits of these volume lead strategies with weights based solely on return information. Finally, we use both returns and volume information to calculate our weights.

4.4.1 The Data

The data used in this study came from the Center of Research in Security Prices (CRSP). We use the weekly (Wednesday to Wednesday) series of returns and volume of all individual stocks that have been continually listed on the CRSP from July 2, 1962 to December 31, 1992 and do not have more than twenty consecutive days of missing data or more than twenty consecutive days of no trading. There are 474 stocks that satisfy these requirements. In order to study the results by stock size, we divide the data into five quintiles determined by their market capitalization value in the middle of the sample period. Weekly sampling was chosen in order to avoid problems due to return and volume characteristics that typically differ by day of the week and to follow suit of other papers in the field. The measure used for market turnover is the one produced in Llorente (1995).[8] Market turnover is defined as the arithmetic mean of all the turnovers for all of the firms with valid records on CRSP on that considered day.

4.4.2 Volume Lead Results

This section evaluates the profitability of the portfolios described in the previous section. The weights were based on the previous volume variables, as defined above. The profits for the four basic portfolios (combinations of positive and negative returns and high and low volume) are returns to the invested dollar. The profits for the combined portfolios (positive return, negative return, high volume, and low volume, and total profits) are *real* profits because these portfolios are zero net investment (costless) portfolios.

Table 4.1 (panel A) in appendix 4.8 presents the main results for the first strategy. The table reports the profits for one week lags. It considers the profits for all of the stocks in the sample and for different size stocks labeled as smallest, medium, and largest quintiles. The t statistics are presented in parenthesis.[9] All of these calculations ignore transaction costs, which will be considered later.

The results in Table 4.1 (panel A) sharply reject the price reversal hypothesis for those stocks with lower than market volume (independently of the return). The returns on these two portfolios are negative and significantly different from zero. Those stocks with higher than market volume and negative returns in period $t-k$ experience price reversal and for those with positive return we cannot reject the null

[8]The reader is suggested to refer to that paper for a complete explanation of the methodology used to calculate this volume measure.

[9]The t statistics are computed using Newey-West corrected standard errors.

hypothesis of *no* price reversal. When looking at the division of stocks by size, the results are quite similar, with striking persistence of stocks in the smallest quintile.

Thus, it seems that as Campbell *et al.* (1993) postulate, stocks with high volume and declines in price experience price reversals, but contrary to their results, stocks with low volume also experience price reversals. By observing the profits of any of the costless portfolios, they are positive for negative returns and for high volume. As we mentioned above, this result comes from the high volume negative return stocks. Even if some of the portfolios produce negative profits, the total combined portfolio produces a positive profit primarily derived from the low return, high volume stocks. Thus, the low return, high volume stocks profits are very high compared to other losing portfolios and outweigh the negative profits of those portfolios.

The analysis of the total profit by stock size reveals that these patterns are more important for smaller and medium size stocks than for larger stocks, as Blume *et al.* (1994) conjecture and Llorente (1995) demonstrates in another context.

Panel A of tables 4.2, 4.3, 4.4, and 4.5 produce the results for the strategies using different lag lengths ($k = 2, 4$, and 26). All of the calculations where performed with non-overlapping periods. The longer lagged periods are provided for interest, although one does not expect this to be testing for volume's informational content, since this is a relatively short-lived phenomenon. However, one can see that the results seem to hold even over a relatively longer time period. The persistence in the structure of profits for negative return stocks (regardless of high or low volume with respect to the market) shows up even in the lags of 26 weeks. Another striking result is that the total profit of the whole costless strategy is positive and significant for lags of two weeks and four weeks. These profits are higher than for one week lags. Analyzing the individual portfolios that induce this result, we observe that it comes again primarily from the stocks in the negative return and high volume. The return from this particular portfolio is higher than it was with a one week lag, and it offsets the portfolios that produce negative returns. The profits of the portfolios with positive returns ($R > 0$)in period $t - k$ are not significantly different from zero.

We observe the same patterns when concentrating only on stocks of a certain size, and continue to witness the strong persistence of smaller quintile stocks.

Tables 4.6, 4.7, and 4.8 present other interesting statistics. Tables 4.6 and 4.7 present the mean investment per stock and period for the different portfolios. That is, how much of our one dollar investment we allocate to each stock within the particular portfolio. Table 4.8 presents the mean number of stocks per portfolio and over time.[10] Analyzing both tables together, we notice that a major proportion of our dollar investments are in stocks with higher than market volume, although evenly distributed among high and low return stocks. These results are artifacts of our data, which has more stocks with low or equal to market volume. We do not believe that the data will produce bias in our final results, because the investment per stock in a particular portfolio depends on the number of stocks in that portfolio (normalization factor) and on the deviation of its turnover from the market turnover.

A major conclusion from this purely volume lead strategy is that there exists price reversal for high volume stocks as postulated by Campbell *et al.* (1993) but there is inconclusive evidence about the "less probable" price reversal for low volume stocks. In fact, with our strategies and our sample, we find that there are price reversals with low volume stocks as well.

Another major conclusion is related to the main hypothesis of the article: the informational content of trading volume. It is clear that for high volume stocks, the information present in volume is able to signal the reversal of prices and produce positive profits for the individual portfolios and the in the global portfolio.

[10]The distribution of the stocks among the portfolios for different lags are similar to the ones presented in Table 4.8. This is an artifact of the non-overlapping construction of the strategies for different lags.

4.4.3 The Volume Lead Strategy with Return Only Based Weights

This section evaluates the profitability of the portfolios described in section 4.3. The main difference of this strategy from the volume lead strategy are the weights. In this strategy, as carefully documented in the previous section, the weights are based solely on the returns of the previous period, but still keeping the same classification of stocks in each portfolio. As before, the results represent returns to our dollar investments in the separate portfolios and profits to our combined portfolios.

This weight scheme has two important characteristics. First, contrary to the volume lead weights, the profits from the strategies followed here are based only on the autocorrelations of the individual returns. Volume is only an indicator variable; we assign it an "identification" function as in Campbell *et al.* (1993). Second, the comparisons of the results from these strategies with the volume lead strategies allow us to access the main hypothesis concerning the informational content of volume, separately from its "identification" role. As the reader will notice, the definitions of positive and negative returns and high and low volume for all securities are independent of the weight scheme. Thus, comparisons of profits among different weight schemes are perfectly valid.

Table 4.1 (panel B) presents the main results from this strategy. The table reports profits for one week lags for different portfolios as before. Panel B of tables 4.2, 4.3, 4.4 and 4.5 present the same information as Table 4.1 (panel B) but for different lag lengths.

The major results about the price reversal hypothesis found in the former strategies apply here as well. Low volume stocks experience price reversal, contrary to what the theory would predict, and high volume stocks, as theory predicts, experiences price reversals as well. It is interesting to note that the profits for the positive return and high volume stocks are significant for all stocks and for the smallest stocks for a lag length of one week, whereas in the volume lead case they were not. One could argue that because the strategy followed in this portfolio is contrarian in returns, the results really reflect the negative autocorrelation produced by the bid-ask for the smaller sized stocks. Even if this argument is credible, we do not think that the bid-ask spread is so important. First, the results of Lo and MacKinley (1991) about the bid-ask spread suggest that this spread does not have any major influence on the final results.[11] Second, with that line of reasoning, the strategy would only produce significant profits for the smallest stocks and not for the others in the case of negative returns and low volume, unless the information produced by the "identification" function assigned to volume is so important as to offset that fact. In any case, the importance of volume information for the high volume stocks is present.

The informational content contained in the volume variable, besides that of "identification", is clear when comparing the results in this section with those of the volume lead section. The profits for the individual portfolios have the same qualitative patterns and very similar quantitative results, independently of the stocks size or lag. The major differences are related to the magnitude of the profits for the individual portfolios, when positive they are greater with the weight scheme used in this section, and when negative, they are also more negative. In other words, this strategy produces profits that are of greater magnitude than in the volume lead strategy case. This also causes the profits for the global portfolios to be smaller with this weight scheme than with the weight scheme based on the volume lead strategy.

4.4.4 The Volume Lead Strategy with Volume and Return Based Weights

This section evaluates the profitability of the other portfolios described in section 4.3, specifically VLR1 and VLR2. The main difference of these strategies from the two mentioned above are again in the weight calculations. In these strategies, the weights

[11] The reader should realize the strong similarity between our sample and their sample.

are based on a combination of returns and volume of the previous period. Again, the results represent returns to our dollar investments in the four basic portfolios and profits to our combined portfolios. Panel C and D of tables 4.1, 4.2, 4.3, 4.4, and 4.5 present the main results for these weight schemes for different lags and stock sizes. The comparison of the results from these weighting schemes to the other two weighting schemes used above make it possible to address simultaneously the joint informational content of both volume and returns and their individual informational content.

The major results about the price reversal hypothesis found before in the other strategies apply here as well. High volume stocks experience reversal as do low volume stocks.

The most important result concerns the comparisons of profits with the other weight schemes. Observing panels A, B, C, and D of the mentioned tables we see that the general pattern structure is similar for all of them, independently of the lag period or stock size. The only two major differences worth noting is the change in high volume stocks with positive returns for lag length one. For this weighting scheme we find clear evidence of price reversal and positive profits. The other important difference is the profit for the global portfolio. For the first weighting scheme (the volume lead strategy), global profits are mainly positive and when significant, produce the highest profit among the four strategies. It seems that information impounded in the volume weight scheme is able to produce global profits even when the other two weighting schemes do not produce profits.

Comparing the profits from the four weighting schemes that include returns, we observe how the joint consideration of volume and returns matters. If volume only modifies the return information (see strategy VLR2, panel D), it does not matter too much. That is, volume does not add much information to that already presented in returns (see Panel B). Contrarily, if volume has its own presence in the covariance structure (strategy VLR1, panel C), it matters a lot and the profits are greater than those with returns alone (see panel B), as postulated by Blume *et al.* (1994).

4.4.5 Other Issues

In this section we would like to briefly address several issues that have already been mentioned in the exposition but not adequately explained. The issues are the following: the possible influence of the bid-ask spread, the transaction costs, the connection of the results with those in Campbell *et al.* (1993) and Llorente (1995), and the results of the strategies when they are contrarian based.

Though the bid-ask spread can be responsible for some of the results using the last two strategies we have presented, we, following the arguments of Lo and Mackinley (1990) and Lehmann (1990), do not think it is a major problem in our study. The results for the first strategy and their comparison with those for the two others support these arguments.

As in all the studies of this nature, our profits are calculated without considering the transaction costs due to the rebalancing of portfolios every period. In order to avoid this problem, and following Lehmann (1990), we calculated the same profits subtracting from the portfolios five percent of the absolute difference between weights in two consecutive periods ($\pi_{it}(k) - 0.05|u_{it}(k) - u_{it-1}(k)|$). All of these profits for every portfolio were negative. This result has been documented in other papers as well. Few of the returns to the portfolio strategies in this article exceed five percent, those that do tend to be for longer horizons and for smaller stock sizes. Therefore these profits, while being statistically and economically significant, may not be true profit measures for an individual investor.

There is an issue concerning the relationship between our results with those of Campbell *et al.* (1993) and Llorente (1995). Though these other authors' scenarios are not directly comparable to ours, because of the specification and risk problems mentioned above, the profits for our second, third, and particularly fourth strategies are directly related to the first autocorrelation of individual returns. For those stocks with positive return, we find evidence of the results from the above mentioned studies: the first autocorrelation is lower on high volume days than on low volume days, and its significance varies with the stock size.

The last issue concerns the comparisons of the profits of our strategies to those obtained with the same weighting schemes but behaving contrarian based on returns in period $t-k$. This essentially removes the identification function assigned to volume, but still considers the information that volume can carry. From this comparison we are able to to analyze the volume information from a different perspective and to compare our results with some other studies in the literature. Table 4.9 presents the results for different weight schemes used by several authors. Though the results are qualitatively similar, one will notice that the actual weight scheme used has a great deal of influence on the quantitative results.

When comparing the profits of the pure contrarian for all strategies to those in which contrarian, is only executed in the high volume situation (see the last two columns of tables 4.1 to 4.5), we find what could have been inferred from the previous results: the price reversal pattern found in all volume situations (high or low) produces higher profits for the contrarian based weights. Among the different weight schemes, the higher profits come from considering only returns or returns and volume combined (strategy VLR1). Once again, we see how the information in trading volume can improve that already contained in returns.

4.5 Conclusion

In this chapter we have documented the importance of the information carried by trading volume and how different it is from that carried in the return variable, as conjectured by Blume *et al.* (1994). In order to test for this hypothesis and to avoid any structural specification a priori, we address the problem by implementing four trading strategies in the spirit of the contrarian trading strategy literature, and following the results of Campbell *et al.* (1993). As a by-product of the design in the strategies, we are able to test for the "identification" function of the volume variable as postulated in Campbell *et al.* (1993). With this specification we lose control of the risk of our portfolios at every period of time, but gain flexibility on the functional form.

The main results of the chapter are as follows. Trading volume has information different from that carried by returns. The portfolio profits from the strategies based on volume or returns alone have the same qualitative and but different quantitative patterns, which are in turn different to the patterns from a strategy consisting of both return and volume information. These results are independent of stock size and lag length in the information transition.

The second major result of the chapter is that the price of high volume stocks tend to reverse as well as those for low volume stocks. Once again, the results are robust to stock size and lag length.

4.6 References

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4.7 Appendix I: Mathematical Derivations

Derivation of Equation 4.7

$$\bar{\pi}_t(k) = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k} - \gamma_{mt-k})R_{it} \tag{4.14}$$

$$= \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k} - \frac{N_p}{N}\gamma_{pt-k} - \frac{N_d}{N}\gamma_{dt-k})(R_{it} + R_t^p - R_t^p) \tag{4.15}$$

$$= \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k} - \frac{N_p}{N}\gamma_{pt-k})(R_{it} - R_t^p) \underbrace{-\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\Omega_{d,pt-k}(R_{it} - R_t^p)}_{=0} +$$

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k} - \gamma_{mt-k})R_t^p \tag{4.16}$$

$$= -\frac{1}{T}\sum_{t=1}^{T}N_p(\gamma_{t-k}^p - \bar{\gamma}^p)(R_t^p - \bar{R}^p) + \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k} - \bar{\gamma}^p)(R_{it} - \bar{R}^p) +$$

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k} - \gamma_{mt-k})R_t^p \tag{4.17}$$

$$= -\frac{1}{T}\sum_{t=1}^{T}N_p(\gamma_{t-k}^p - \bar{\gamma}^p)(R_t^p - \bar{R}^p) + \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k} - \bar{\gamma}_i)(R_{it} - \bar{R}_i) +$$

$$\sum_{i=1}^{N_p}(\bar{\gamma}_i - \bar{\gamma}^p)(\bar{R}_i - \bar{R}^p) + \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k} - \gamma_{mt-k})R_t^p, \tag{4.18}$$

where $\Omega_{d,pt-k} = \frac{N_d}{N}\frac{\sum_{i=1}^{N_d} V_{it-k}}{\sum_{i=1}^{N_p}(V_{it-k} - V_{mt-k})}$ is a measure of the weighted volumes of securities traded that are outside of the specific portfolio, yet part of the N total securities divided by the familiar volume weighting for that portfolio.

Derivation of Equation 4.17

It will be sufficient to show that:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k}-\gamma_{pt-k})(R_{it}-R_t^p) = -\frac{1}{T}\sum_{t=1}^{T}N_p(\gamma_{t-k}^p-\bar{\gamma}^p)(R_t^p-\bar{R}^p)+ \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k}-\bar{\gamma}^p)(R_{it}-\bar{R}^p). \quad (4.19)$$

$$\begin{aligned} LHS: &= \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k}-\frac{N_p}{N}\gamma_{t-k}^p)(R_{it}-R_t^p) \\ &= \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}[\gamma_{it-k}R_{it}-\gamma_{it-k}R_t^p-\frac{N_p}{N}\gamma_{t-k}^pR_{it}+\frac{N_p}{N}\gamma_{t-k}^pR_t^p] \\ &= \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\gamma_{it-k}R_{it}-\frac{1}{T}\sum_{t=1}^{T}N_p\gamma_{t-k}^pR_t^p. \\ RHS: &= -\frac{1}{T}\sum_{t=1}^{T}N_p(\gamma_{t-k}^p-\bar{\gamma}^p)(R_t^p-\bar{R}^p)+\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k}-\bar{\gamma}^p)(R_{it}-\bar{R}^p) \\ &= \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\gamma_{it-k}R_{it}-\frac{1}{T}\sum_{t=1}^{T}N_p\gamma_{t-k}^pR_t^p+N_p\bar{\gamma}^p\bar{R}^p-N_p\bar{\gamma}^p\bar{R}^p \\ &= \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\gamma_{it-k}R_{it}-\frac{1}{T}\sum_{t=1}^{T}N_p\gamma_{t-k}^pR_t^p. \end{aligned}$$

□

Derivation of Equation 4.18

It will be sufficient to show that:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k}-\bar{\gamma}^p)(R_{it}-\bar{R}^p) = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k}-\bar{\gamma}_i)(R_{it}-\bar{R}_i)+ \sum_{i=1}^{N_p}(\bar{\gamma}_i-\bar{\gamma}^p)(\bar{R}_i-\bar{R}^p). \quad (4.20)$$

$$LHS: = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k}-\bar{\gamma}^p)(R_{it}-\bar{R}^p)$$

$$= \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}[\gamma_{it-k}R_{it} - \gamma_{it-k}\bar{R}^p - \bar{\gamma}^p R_{it} + \bar{\gamma}^p\bar{R}^p]$$

$$= \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\gamma_{it-k}R_{it} - N_p\bar{\gamma}^p\bar{R}^p.$$

$$RHS: \; = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}(\gamma_{it-k} - \bar{\gamma}_i)(R_{it} - \bar{R}_i) + \sum_{i=1}^{N_p}(\bar{\gamma}_i - \bar{\gamma}^p)(\bar{R}_i - \bar{R}^p)$$

$$= \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\gamma_{it-k}R_{it} - \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\gamma_{it-k}\bar{R}_i - \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\bar{\gamma}_i R_{it} + \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\bar{\gamma}_i\bar{R}_i$$

$$+\sum_{i=1}^{N_p}[\bar{\gamma}_i\bar{R}_i - \bar{\gamma}_i\bar{R}^p - \bar{\gamma}^p\bar{R}_i + \bar{\gamma}^p\bar{R}^p]$$

$$= \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\gamma_{it-k}R_{it} \underbrace{- \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\gamma_{it-k}\bar{R}_i + \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\bar{\gamma}_i\bar{R}_i}_{=0}$$

$$\underbrace{-\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\bar{\gamma}_i R_{it} + \sum_{i=1}^{N_p}\bar{\gamma}_i\bar{R}_i}_{=0} - N_p\bar{\gamma}^p\bar{R}^p$$

$$= \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_p}\gamma_{it-k}R_{it} - N_p\bar{\gamma}^p\bar{R}^p. \qquad \square$$

The reader should be aware that the terms in underbraces are only equal to zero if the summations can be reversed, that is if N_p is independent across time. With our strategies, this is not so. Hence we cannot make the decomposition from equation 4.17 to equation 4.18. We left this step in for those who deal with a constant N over time.

4.8 Appendix II: Tables

Table 4.1: Mean Profits of All Four Strategies

Portfolio	$R>0$ $V>V_m$	$R>0$ $V<V_m$	$R<0$ $V>V_m$	$R<0$ $V<V_m$	$R>0$	$R<0$	$V>V_m$	$V<V_m$	Total Profit	Contrarian Profit
Panel A: Using the Volume Lead Strategy										
All Stocks	-0.285	-1.35	7.38	-1.92	-1.63	5.46	7.09	-3.2	3.82	10.38
	(-0.289)	(-2.42)	(7.667)	(-3.22)	(-2.296)	(7.89)	(8.12)	(-13.68)	(4.323)	(11.18)
Smallest	0.114	-3.7	12.75	-3.86	-3.58	8.8	12.8	-7.57	5.29	20.45
	(0.0741)	(-4.923)	(8.904)	(-4.44)	(-2.74)	(7.20)	(7.42)	(-13.82)	(2.94)	(11.15)
Medium	-0.124	-0.578	5.17	-1.23	-0.702	3.94	5.05	-1.8	3.23	6.88
	(-0.1216)	(-0.99)	(4.789)	(-2.207)	(-0.7752)	(4.32)	(4.03)	(-4.73)	(2.507)	(5.17)
Largest	-0.71	-0.621	4.365	-1.68	-1.34	2.67	3.6	-2.3	1.337	5.96
	(-0.716)	(-1.121)	(4.23)	(-2.964)	(-1.54)	(3.07)	(3.17)	(-6.70)	(1.12)	(4.94)
Panel B: Using Volume as an Indicator and Returns as Weights										
All Stocks	2.63	-3.77	10.66	-7.77	-1.14	2.89	13.29	-11.55	1.75	24.87
	(2.916)	(-5.531)	(11.264)	(-4.965)	(-1.847)	(1.890)	(17.133)	(-7.888)	(1.077)	(14.74)
Smallest	3.34	-8.09	15.7	-13.53	-4.7	2.19	19.07	-21.6	-2.55	40.73
	(2.266)	(-8.41)	(11.579)	(-5.077)	(-3.66)	(0.82)	(11.73)	(-8.26)	(-0.844)	(12.97)
Medium	1.102	-1.94	6.648	-3.866	-0.84	2.78	7.75	-5.8	1.93	13.57
	(1.18)	(-2.66)	(6.345)	(-5.483)	(-0.96)	(3.14)	(6.80)	(-8.79)	(1.504)	(10.08)
Largest	0.53	-0.73	4.58	-3.94	-0.207	0.639	5.115	-4.68	0.432	9.81
	(0.60)	(-1.269)	(4.268)	(-5.964)	(-0.28)	(0.70)	(4.64)	(-10.15)	(0.3699)	(8.04)
Panel C: Using the Volume Lead Strategy Combined with Return Information (VLR1)										
All Stocks	2.37	-4.14	12.4	-7.53	-1.77	4.89	14.8	-11.6	3.126	26.50
	(1.87)	(-0.027)	(9.73)	(-4.118)	(-1.63)	(2.43)	(9.73)	(-6.659)	(1.357)	(11.32)
Smallest	2.07	-8.57	17.1	-12.7	-6.5	4.3	19.2	-21.3	-2.12	40.62
	(1.07)	(-8.81)	(10.83)	(-4.459)	(-3.54)	(1.43)	(8.50)	(-7.51)	(-0.0579)	(11.24)
Medium	1.33	-1.68	6.56	-2.98	-0.34	3.58	7.89	-4.6	3.23	12.57
	(1.164)	(-2.202)	(5.239)	(-4.24)	(-0.30)	(3.06)	(5.10)	(-6.45)	(1.90)	(7.33)
Largest	-0.08	-0.88	5.244	-3.359	-0.96	1.88	5.16	-4.2	0.924	9.41
	(-0.073)	(-1.49)	(4.44)	(-5.1135)	(-0.94)	(1.81)	(3.86)	(-9.14)	(0.0639)	(6.64)
Panel D: Using the Volume Lead Strategy Combined with Return Information (VLR2)										
All Stocks	2.65	-3.78	10.67	-7.78	-1.14	2.90	13.32	-11.56	1.76	24.87
	(2.93)	(-5.54)	(11.26)	(-4.97)	(-1.85)	(1.89)	(17.15)	(-7.89)	(1.08)	(14.73)
Smallest	3.33	-8.10	15.75	-13.55	-4.77	2.20	19.08	-21.65	-2.57	40.72
	(2.25)	(-8.42)	(11.58)	(-5.08)	(-3.67)	(0.823)	(11.70)	(-8.26)	(-0.848)	(12.96)
Medium	1.10	-1.95	6.65	-3.87	-0.844	2.78	7.75	-5.82	1.94	13.57
	(1.18)	(-2.67)	(6.34)	(-5.48)	(-0.964)	(3.14)	(6.79)	(-8.79)	(1.50)	(10.07)
Largest	0.531	-0.739	4.59	-16.68	-0.208	-12.10	5.12	-17.42	-12.30	9.81
	(0.603)	(-1.27)	(4.27)	(-1.66)	(-0.281)	(-1.20)	(4.64)	(-1.74)	(-1.22)	(8.04)

These are all the returns and profits from various strategies using a one week lag, that is $k = 1$. The reader should realize that the various portfolios are shorthands for the strategies, thus $R > 0$ and $V > V_m$ indicates the portfolio of stocks for which the individual stock return was greater than zero and the individual volume was greater than market volume at $t - k$. The other portfolios are as discussed in the section 4.3 of chapter 4. The $R > 0$ portfolio indicates the combined profits from the portfolios with positive return in period $t - k$, yet still using the weights as defined by each strategy. Similarly, the $R < 0$ portfolio indicates the combined profits from the portfolios with negative return in period $t - k$. The $V > V_m$ portfolio is the combined profits from the high volume stocks in period $t - k$ using the weights described by the strategy. The $V < V_m$ portfolio is the combined profits from the low volume stocks in period $t - k$ using the weights described by the respective strategy. Total profit is the sum of returns of the four portfolios of each strategy. It is a costless portfolio, and it represents true profits. The contrarian profits indicate the profits from using the same strategies as outlined in section 4.3 however, we change them so as to sell winner stocks ($R > 0$) and buy loser stocks ($R < 0$); this is also a costless portfolio. The t statistics presented in the parentheses are Newey-West corrected using four lags. The sample consists of 1559 weeks. The returns and profits presented have been multiplied by 1000.

Table 4.2: Mean Profits of All Four Strategies for Lags $k = 2, 4$, and 26: All Stocks

Lag	$R>0$ $V>V_m$	$R>0$ $V<V_m$	$R<0$ $V>V_m$	$R<0$ $V<V_m$	$R>0$	$R<0$	$V>V_m$	$V<V_m$	Total Profit	Contrarian Profit
Panel A: Using the Volume Lead Strategy										
2	-0.2	-1.7	11.2	-4.41	-1.9	7.0	10.9	-5.9	5.0	16.86
	(-0.138)	(-1.496)	(5.358)	(-3.223)	(1.422)	(4.869)	(6.262)	(11.23)	(2.833)	(9.00)
4	-1.1	0.4	17.3	-7.6	-0.7	9.7	16.2	-7.2	9.0	23.46
	(-0.305)	(0.177)	(3.636)	(-2.944)	(0.292)	(2.803)	(4.125)	(6.887)	(2.263)	(5.64)
26	-2.9	12.7	31.2	-44.2	9.8	-13.0	28.2	-31.4	-3.2	59.74
	(-0.121)	(1.404)	(1.602)	(-3.371)	(0.528)	(1.058)	(1.595)	(4.432)	(-0.173)	(3.02)
Panel B: Using Volume as an Indicator and Returns as Weights										
2	0.8	-4.2	12.8	-10.1	-3.4	2.7	13.6	-14.3	-0.7	28.03
	(0.260)	(-3.029)	(7.040)	(-5.111)	(-1.172)	(1.686)	(4.623)	(-9.006)	(-0.208)	(8.06)
4	-2.3	-3.1	21.0	-12.2	-5.4	8.7	18.6	-15.3	3.3	34.01
	(-0.666)	(-1.220)	(3.889)	(-4.059)	(-2.428)	(2.191)	(4.232)	(-9.070)	(0.767)	(6.68)
26	-19.4	29.78	48.4	-57.8	10.3	-9.3	29.0	-28.0	1.0	57.09
	(-0.984)	(1.793)	(2.117)	(-3.735)	(0.492)	(-0.655)	(1.349)	(-1.9228)	(0.0417)	(2.04)
Panel C: Using the Volume Lead Strategy Combined with Return Information (VLR1)										
2	-1.1	-4.6	15.2	-9.7	-5.8	5.4	14.0	-14.4	-0.4	28.49
	(-0.255)	(-3.394)	(5.979)	(-4.421)	(1.261)	(2.159)	(2.920)	(7.654)	(-0.0776)	(5.34)
4	0.1	-3.6	32.2	-10.7	-3.4	21.4	32.3	-14.3	18.0	46.75
	(0.036)	(-1.474)	(2.902)	(-3.583)	(1.033)	(2.089)	(2.911)	(8.567)	(1.622)	(4.10)
26	-6.1	11.1	38.9	-56.9	4.9	-18.0	32.8	-45.0	-13.0	78.78
	(-0.222)	(1.180)	(1.571)	(-3.904)	(0.231)	(1.052)	(1.362)	(4.616)	(-0.595)	(2.65)
Panel D: Using the Volume Lead Strategy Combined with Return Information (VLR2)										
2	0.804	-4.23	12.89	-10.12	-3.43	2.77	13.69	-14.35	-0.660	28.04
	(0.261)	(-3.03)	(7.04)	(-5.11)	(-1.17)	(1.69)	(4.62)	(-9.01)	(-0.204)	(8.05)
4	-2.33	-3.08	21.09	-12.26	-5.41	8.83	18.76	-15.35	3.42	34.11
	(-0.655)	(-1.22)	(3.88)	(-4.06)	(-2.41)	(2.19)	(4.23)	(-9.07)	(0.785)	(6.66)
26	-19.34	29.80	48.40	-57.83	10.46	-9.43	29.06	-28.03	1.03	57.09
	(-0.978)	(1.79)	(2.11)	(-3.74)	(0.498)	(-0.662)	(1.35)	(-1.93)	(0.043)	(2.04)

These are all the returns and profits from various strategies using two, four, and twenty six week lags, that is $k = 2, 4$, and 26. The reader should realize that the various portfolios are shorthands for the strategies, thus $R > 0$ and $V > V_m$ indicates the portfolio of stocks for which the individual stock return was greater than zero and the individual volume was greater than market volume at $t - k$. The other portfolios are as discussed in the section 4.3 of chapter 4. The $R > 0$ portfolio indicates the combined profits from the portfolios with positive return in period $t - k$, yet still using the weights as defined by each strategy. Similarly, the $R < 0$ portfolio indicates the combined profits from the portfolios with negative return in period $t - k$. The $V > V_m$ portfolio is the combined profits from the high volume stocks in period $t - k$ using the weights described by the strategy. The $V < V_m$ portfolio is the combined profits from the low volume stocks in period $t - k$ using the weights described by the respective strategy. Total profit is the sum of returns of the four portfolios of each strategy. It is a costless portfolio, and it represents true profits. The contrarian profits indicate the profits from using the same strategies as outlined in section 4.3 however, we change them so as to sell winner stocks ($R > 0$) and buy loser stocks ($R < 0$); this is also a costless portfolio. The t statistics presented in the parentheses are Newey-West corrected using four lags. The sample consists of 1559 weeks. The returns and profits presented have been multiplied by 1000.

Table 4.3: Mean Profits of All Four Strategies for Lags $k = 2, 4$, and 26: Largest Quintile

Lag	$R > 0$ $V > V_m$	$R > 0$ $V < V_m$	$R < 0$ $V > V_m$	$R < 0$ $V < V_m$	$R > 0$	$R < 0$	$V > V_m$	$V < V_m$	Total Profit	Contrarian Profit
Panel A: Using the Volume Lead Strategy										
2	-2.90	-0.161	7.05	-2.66	-3.06	4.39	4.16	-2.82	1.33	6.98
	(-1.38)	(-0.161)	(3.32)	(-2.44)	(-1.65)	(2.40)	(1.81)	(-4.24)	(0.563)	(2.89)
4	-6.06	2.13	13.56	-4.75	-3.94	8.81	7.50	-2.62	4.87	10.12
	(-1.63)	(1.02)	(3.07)	(-2.27)	(-1.22)	(2.51)	(1.69)	(-1.83)	(1.08)	(2.09)
26	-6.30	5.36	71.63	-37.64	-0.934	34.00	65.35	-32.28	33.07	97.62
	(-0.318)	(0.623)	(2.86)	(-3.11)	(-0.048)	(1.44)	(2.63)	(-3.33)	(1.29)	(3.54)
Panel B: Using Volume as an Indicator and Returns as Weights										
2	-1.08	-0.517	7.91	-4.98	-1.60	2.92	6.82	-5.50	1.32	12.32
	(-0.570)	(-0.460)	(4.04)	(-3.95)	(-0.987)	(1.77)	(3.29)	(-6.12)	(0.610)	(5.25)
4	-5.57	2.60	13.46	-5.70	-2.98	7.76	7.89	-3.10	4.79	10.99
	(-1.65)	(1.17)	(3.41)	(-2.41)	(-1.05)	(2.50)	(2.07)	(-1.77)	(1.22)	(2.47)
26	-20.29	8.14	77.11	-46.20	-12.41	30.92	56.83	38.06	18.77	94.88
	(-0.979)	(0.758)	(3.11)	(-4.40)	(-0.653)	(1.47)	(2.11)	(-3.70)	(0.740)	(2.97)
Panel C: Using the Volume Lead Strategy Combined with Return Information (VLR1)										
2	-2.96	-0.911	8.60	-4.42	-3.87	4.18	5.64	-5.33	0.308	10.97
	(-1.34)	(-0.837)	(3.78)	(-3.58)	(-1.97)	(2.02)	(2.20)	(-5.85)	(0.116)	(3.93)
4	-6.70	1.44	15.00	-5.31	-5.26	9.70	8.31	-3.87	4.44	12.18
	(-1.62)	(0.641)	(3.15)	(-2.26)	(-1.45)	(2.39)	(1.65)	(-2.09)	(0.868)	(2.18)
26	-13.42	3.27	96.14	-44.77	-10.15	51.37	82.72	-41.50	41.22	24.23
	(-0.471)	(0.305)	(3.54)	(-4.12)	(-0.356)	(2.18)	(2.62)	(-4.05)	(1.36)	(3.45)
Panel D: Using the Volume Lead Strategy Combined with Return Information (VLR2)										
2	-1.09	-0.517	7.91	-4.98	-1.60	2.92	6.82	-5.50	1.32	12.32
	(-0.571)	(-0.460)	(4.04)	(-3.95)	(-0.987)	(1.77)	(3.29)	(-6.12)	(0.610)	(5.25)
4	-5.58	2.60	13.46	-5.70	-2.98	7.76	7.88	-3.10	4.78	10.99
	(0.067)	(1.16)	(3.40)	(-2.41)	(-1.05)	(2.50)	(2.07)	(-1.77)	(1.22)	(2.47)
26	-20.25	8.14	77.15	-46.20	-12.11	30.96	56.90	-38.05	18.85	94.96
	(-0.978)	(0.758)	(3.11)	(-4.40)	(-0.650)	(1.47)	(2.11)	(-3.70)	(0.743)	(2.97)

These are all the returns and profits from various strategies using two, four, and twenty six week lags, that is $k = 2, 4$, and 26. The reader should realize that the various portfolios are shorthands for the strategies, thus $R > 0$ and $V > V_m$ indicates the portfolio of stocks for which the individual stock return was greater than zero and the individual volume was greater than market volume at $t - k$. The other portfolios are as discussed in the section 4.3 of chapter 4. The $R > 0$ portfolio indicates the combined profits from the portfolios with positive return in period $t - k$, yet still using the weights as defined by each strategy. Similarly, the $R < 0$ portfolio indicates the combined profits from the portfolios with negative return in period $t - k$. The $V > V_m$ portfolio is the combined profits from the high volume stocks in period $t - k$ using the weights described by the strategy. The $V < V_m$ portfolio is the combined profits from the low volume stocks in period $t - k$ using the weights described by the respective strategy. Total profit is the sum of returns of the four portfolios of each strategy; it is a costless portfolio. It represents tr strategy. It is a costless portfolio, and it represents true profits. The contrarian profits indicate the profits from using the same strategies as outlined in section 4.3 however, we change them so as to sell winner stocks ($R > 0$) and buy loser stocks ($R < 0$); this is also a costless portfolio. The t statistics presented in the parentheses are Newey-West corrected using four lags. The sample consists of 1559 weeks. The returns and profits presented have been multiplied by 1000.

Table 4.4: Mean Profits of All Four Strategies for Lags $k = 2, 4$, and 26: Medium Quintile

Lag	$R > 0$ $V > V_m$	$R > 0$ $V < V_m$	$R < 0$ $V > V_m$	$R < 0$ $V < V_m$	$R > 0$	$R < 0$	$V > V_m$	$V < V_m$	Total Profit	Contrarian Profit
	Panel A: Using the Volume Lead Strategy									
2	-1.26	-1.30	8.74	-2.67	-2.56	6.07	7.48	-3.98	3.51	11.46
	(-0.632)	(-1.06)	(4.31)	(-2.25)	(-1.39)	(3.64)	(3.25)	(-4.53)	(1.42)	(4.66)
4	-2.62	-0.156	13.82	-6.45	-2.77	7.37	11.20	-6.61	4.60	17.81
	(-0.652)	(-0.073)	(3.15)	(-2.68)	(-0.800)	(1.98)	(2.27)	(-4.43)	(0.897)	(3.45)
26	-6.42	-0.992	15.48	-40.16	-7.41	-24.69	9.06	-41.16	-32.10	50.22
	(-0.253)	(-0.089)	(0.727)	(-2.91)	(-0.341)	(-1.46)	(0.313)	(-4.04)	(-1.19)	(1.48)
	Panel B: Using Volume as an Indicator and Returns as Weights									
2	-1.67	-2.62	7.43	-6.03	-4.29	1.40	5.76	-8.65	-2.89	14.42
	(-0.922)	(-1.82)	(3.64)	(-4.26)	(-2.40)	(0.782)	(2.67)	(-7.15)	(-1.18)	(5.78)
4	-3.10	-2.43	10.13	-10.77	-5.53	-0.643	7.03	-13.20	-6.17	20.23
	(-0.862)	(-1.04)	(2.43)	(-3.25)	(-1.78)	(-0.169)	(1.48)	(-5.39)	(-1.23)	(3.57)
26	-13.79	4.06	35.86	-57.89	-9.73	-22.03	22.07	-53.83	-31.76	75.90
	(-0.683)	(0.332)	(1.46)	(-3.65)	(-0.552)	(-1.13)	(0.785)	(-3.70)	(-0.575)	(2.12)
	Panel C: Using the Volume Lead Strategy Combined with Return Information (VLR1)									
2	-1.21	-2.59	8.69	-4.60	-3.80	4.09	7.48	-7.18	0.295	14.66
	(-0.527)	(-1.67)	(3.82)	(-3.32)	(-1.57)	(1.90)	(2.52)	(-5.12)	(0.053)	(4.48)
4	-1.31	-2.77	12.60	-8.17	-4.08	4.44	11.29	-10.94	0.355	22.23
	(-0.278)	(-1.23)	(2.52)	(-2.90)	(-0.928)	(0.968)	(1.78)	(-5.40)	(0.053)	(3.36)
26	-7.96	0.665	20.24	-51.55	-7.30	-31.31	12.28	-50.88	-3.86	63.17
	(-0.317)	(0.051)	(0.811)	(-3.23)	(-0.342)	(-1.56)	(0.377)	(-3.59)	(-1.25)	(1.60)
	Panel D: Using the Volume Lead Strategy Combined with Return Information (VLR2)									
2	-1.66	-2.62	7.43	6.45	-4.28	13.88	5.77	3.83	9.60	14.43
	(-0.917)	(-1.82)	(3.64)	(0.521)	(-2.39)	(1.09)	(2.67)	(0.306)	(0.753)	(5.78)
4	-3.06	-2.43	10.14	-10.77	-5.49	-0.637	7.07	-13.20	-6.13	20.27
	(-0.851)	(-1.04)	(2.43)	(-3.25)	(-1.76)	(-0.168)	(1.48)	(-5.39)	(-1.22)	(3.57)
26	-13.81	4.07	35.83	-5.79	-9.74	-22.07	22.02	-53.83	-31.81	75.85
	(-0.683)	(0.332)	(1.46)	(-3.65)	(-0.552)	(-1.13)	(0.782)	(-3.70)	(-1.18)	(2.12)

These are all the returns and profits from various strategies using two, four, and twenty six week lags, that is $k = 2, 4$, and 26. The reader should realize that the various portfolios are shorthands for the strategies, thus $R > 0$ and $V > V_m$ indicates the portfolio of stocks for which the individual stock return was greater than zero and the individual volume was greater than market volume at $t - k$. The other portfolios are as discussed in the section 4.3 of chapter 4. The $R > 0$ portfolio indicates the combined profits from the portfolios with positive return in period $t-k$, yet still using the weights as defined by each strategy. Similarly, the $R < 0$ portfolio indicates the combined profits from the portfolios with negative return in period $t - k$. The $V > V_m$ portfolio is the combined profits from the high volume stocks in period $t - k$ using the weights described by the strategy. The $V < V_m$ portfolio is the combined profits from the low volume stocks in period $t - k$ using the weights described by the respective strategy. Total profit is the sum of returns of the four portfolios of each strategy. It is a costless portfolio, and it represents true profits. The contrarian profits indicate the profits from using the same strategies as outlined in section 4.3 however, we change them so as to sell winner stocks ($R > 0$) and buy loser stocks ($R < 0$); this is also a costless portfolio. The t statistics presented in the parentheses are Newey-West corrected using four lags. The sample consists of 1559 weeks. The returns and profits presented have been multiplied by 1000.

Table 4.5: Mean Profits of All Four Strategies for Lags k = 2, 4, and 26: Smallest Quintile

Lag	$R>0$ $V>V_m$	$R>0$ $V<V_m$	$R<0$ $V>V_m$	$R<0$ $V<V_m$	$R>0$	$R<0$	$V>V_m$	$V<V_m$	Total Profit	Contrarian Profit
Panel A: Using the Volume Lead Strategy										
2	-0.944	-2.78	7.53	-7.37	-3.72	10.16	16.58	-10.14	6.44	26.73
	(-0.292)	(-1.66)	(4.79)	(-3.85)	(-1.28)	(3.21)	(4.08)	(-9.73)	(1.56)	(6.25)
4	1.49	1.44	29.14	-11.60	2.93	17.54	30.63	-10.16	20.48	40.79
	(0.286)	(0.434)	(2.65)	(-3.12)	(0.725)	(1.72)	(2.95)	(-5.35)	(1.92)	(3.90)
26	6.20	47.78	34.84	-58.48	53.98	-23.64	41.04	-10.70	30.34	51.74
	(0.191)	(2.43)	(1.02)	(-2.71)	(2.83)	(-1.02)	(1.33)	(-0.683)	(0.959)	(1.39)
Panel B: Using Volume as an Indicator and Returns as Weights										
2	-1.63	-6.88	17.53	-17.96	-8.51	-0.428	15.90	-24.84	-8.94	40.74
	(-0.186)	(-8.41)	(6.71)	(-4.90)	(-0.937)	(-0.123)	(1.82)	(-7.12)	(-0.943)	(4.35)
4	1.95	-3.66	34.15	-19.27	-1.71	14.88	36.10	-22.93	13.17	59.03
	(0.390)	(-0.916)	(3.47)	(-4.45)	(-0.433)	(1.71)	(3.94)	(-6.86)	(1.41)	(5.81)
26	10.15	85.65	55.40	-67.91	95.80	-12.51	65.55	17.74	83.29	47.80
	(0.318)	(2.15)	(1.41)	(-2.57)	(2.96)	(-0.502)	(1.78)	(0.457)	(2.26)	(0.72)
Panel C: Using the Volume Lead Strategy Combined with Return Information (VLR1)										
2	-3.56	-7.13	18.42	-17.37	-10.68	1.47	14.86	-24.50	-9.64	39.36
	(-0.427)	(-3.37)	(6.23)	(-4.40)	(-1.24)	(0.255)	(1.80)	(-6.50)	(-1.08)	(4.28)
4	4.27	-4.69	39.27	-16.48	-0.422	22.79	43.53	-21.17	22.36	64.70
	(0.760)	(-1.22)	(2.67)	(-3.74)	(-0.089)	(1.64)	(3.04)	(-6.54)	(1.55)	(4.31)
26	16.12	48.58	33.03	-67.86	64.70	-34.84	49.14	-19.28	29.86	68.42
	(0.474)	(2.13)	(0.857)	(-2.47)	(2.52)	(-1.13)	(1.23)	(-0.908)	(0.709)	(1.42)
Panel D: Using the Volume Lead Strategy Combined with Return Information (VLR2)										
2	-1.63	-6.88	17.55	-17.96	-8.51	-0.047	15.92	-24.84	-8.92	40.76
	(-0.187)	(-3.15)	(6.72)	(-4.90)	(-0.938)	(-0.117)	(1.82)	(-7.12)	(-0.942)	(4.35)
4	1.99	-3.66	34.27	53.44	-1.67	87.71	36.25	49.78	86.03	59.19
	(0.099)	(-0.915)	(3.47)	(0.744)	(-0.423)	(1.22)	(3.94)	(0.689)	(1.20)	(5.80)
26	10.22	85.66	55.31	-67.90	95.88	-12.59	65.54	17.76	83.29	47.78
	(0.320)	(2.15)	(1.40)	(-2.57)	(2.96)	(-0.506)	(1.78)	(0.458)	(2.26)	(0.72)

These are all the returns and profits from various strategies using two, four, and twenty six week lags, that is $k = 2, 4$, and 26. The reader should realize that the various portfolios are shorthands for the strategies, thus $R > 0$ and $V > V_m$ indicates the portfolio of stocks for which the individual stock return was greater than zero and the individual volume was greater than market volume at $t - k$. The other portfolios are as discussed in the section 4.3 of chapter 4. The $R > 0$ portfolio indicates the combined profits from the portfolios with positive return in period $t-k$, yet still using the weights as defined by each strategy. Similarly, the $R < 0$ portfolio indicates the combined profits from the portfolios with negative return in period $t - k$. The $V > V_m$ portfolio is the combined profits from the high volume stocks in period $t - k$ using the weights described by the strategy. The $V < V_m$ portfolio is the combined profits from the low volume stocks in period $t - k$ using the weights described by the respective strategy. Total profit is the sum of returns of the four portfolios of each strategy. It is a costless portfolio, and it represents true profits. The contrarian profits indicate the profits from using the same strategies as outlined in section 4.3 however, we change them so as to sell winner stocks ($R > 0$) and buy loser stocks ($R < 0$); this is also a costless portfolio. The t statistics presented in the parentheses are Newey-West corrected using four lags. The sample consists of 1559 weeks. The returns and profits presented have been multiplied by 1000.

Table 4.6: Mean Absolute Weight Invested in Each Stock for All Four Strategies: All Stocks

Portfolio	$R>0$ $V>V_m$	$R>0$ $V<V_m$	$R<0$ $V>V_m$	$R<0$ $V<V_m$	$R>0$	$R<0$	$V>V_m$	$V<V_m$	Global
				Panel A: For All Strategies					
All Stocks	0.027	0.009	0.026	0.006	0.012	0.009	0.020	0.006	0.017
	(0.033)	(0.009)	(0.025)	(0.003)	(0.011)	(0.004)	(0.009)	(0.001)	(0.023)
Smallest	0.130	0.049	0.123	0.025	0.065	0.039	0.095	0.029	0.082
	(0.133)	(0.053)	(0.108)	(0.008)	(0.048)	(0.013)	(0.026)	(0.003)	(0.101)
Medium	0.144	0.045	0.157	0.031	0.060	0.046	0.110	0.029	0.094
	(0.155)	(0.055)	(0.178)	(0.023)	(0.052)	(0.030)	(0.070)	(0.004)	(0.134)
Largest	0.205	0.057	0.198	0.044	0.071	0.056	0.164	0.031	0.126
	(0.258)	(0.100)	(0.254)	(0.063)	(0.099)	(0.057)	(0.191)	(0.010)	(0.205)

These weights are for the calculations using a one week lag, that is $k = 1$. The weights are defined as the mean investment per stock in each portfolio as a fraction of the total dollar investment. The reader should realize that the various portfolios are shorthands for the strategies, thus $R > 0$ and $V > V_m$ indicates the portfolio of stocks for which the individual stock return was greater than zero and the individual volume was greater than market volume at $t-k$. The other portfolios are as discussed in section 4.3 of chapter 4. The $R > 0$ portfolio indicates the combined portfolio from the portfolios with positive return in period $t-k$. Similarly, the $R < 0$ portfolio indicates the combined portfolio from the portfolios with negative return in period $t-k$. The $V > V_m$ portfolio indicates the combined portfolio from the high volume stock portfolios in period $t-k$. Similarly, the $V < V_m$ portfolio indicates the combined portfolio from the low volume stock portfolios in period $t-k$. The standard errors are presented in parentheses. The sample consists of 1559 weeks.

Table 4.7: Mean Absolute Weight Invested in Each Stock for All Four Strategies: Different Lags

Lag	Portfolio	$R>0$ $V>V_m$	$R>0$ $V<V_m$	$R<0$ $V>V_m$	$R<0$ $V<V_m$	$R>0$	$R<0$	$V>V_m$	$V<V_m$	Global
$k=2$	All Stocks	0.027	0.009	0.029	0.006	0.012	0.010	0.020	0.006	0.018
		(0.047)	(0.008)	(0.030)	(0.004)	(0.011)	(0.006)	(0.009)	(0.001)	(0.030)
	Smallest	0.125	0.049	0.129	0.027	0.066	0.043	0.094	0.029	0.085
		(0.127)	(0.053)	(0.116)	(0.013)	(0.061)	(0.021)	(0.026)	(0.003)	(0.049)
	Medium	0.139	0.046	0.171	0.034	0.061	0.050	0.109	0.029	0.098
		(0.150)	(0.065)	(0.203)	(0.026)	(0.061)	(0.033)	(0.069)	(0.004)	(0.046)
	Largest	0.196	0.055	0.194	0.047	0.067	0.060	0.163	0.031	0.124
		(0.243)	(0.089)	(0.256)	(0.069)	(0.086)	(0.077)	(0.188)	(0.010)	(0.200)
$k=4$	All Stocks	0.029	0.010	0.031	0.007	0.014	0.011	0.020	0.006	0.019
		(0.073)	(0.019)	(0.030)	(0.006)	(0.025)	(0.008)	(0.009)	(0.001)	(0.042)
	Smallest	0.131	0.053	0.148	0.030	0.068	0.049	0.094	0.028	0.090
		(0.146)	(0.076)	(0.149)	(0.020)	(0.075)	(0.037)	(0.027)	(0.003)	(0.122)
	Medium	0.131	0.049	0.191	0.042	0.062	0.057	0.109	0.029	0.103
		(0.136)	(0.092)	(0.234)	(0.068)	(0.077)	(0.052)	(0.073)	(0.004)	(0.159)
	Largest	0.186	0.057	0.212	0.052	0.065	0.067	0.168	0.031	0.127
		(0.237)	(0.105)	(0.277)	(0.084)	(0.083)	(0.096)	(0.203)	(0.010)	(0.207)
$k=26$	All Stocks	0.027	0.009	0.055	0.009	0.013	0.014	0.021	0.006	0.025
		(0.034)	(0.011)	(0.137)	(0.013)	(0.015)	(0.021)	(0.010)	(0.001)	(0.074)
	Smallest	0.135	0.073	0.149	0.051	0.087	0.067	0.088	0.028	0.102
		(0.184)	(0.145)	(0.185)	(0.078)	(0.144)	(0.076)	(0.029)	(0.005)	(0.160)
	Medium	0.150	0.046	0.208	0.061	0.065	0.080	0.109	0.028	0.116
		(0.193)	(0.059)	(0.248)	(0.134)	(0.083)	(0.141)	(0.064)	(0.005)	(0.185)
	Largest	0.199	0.039	0.205	0.058	0.051	0.072	0.192	0.029	0.125
		(0.268)	(0.044)	(0.234)	(0.079)	(0.043)	(0.081)	(0.236)	(0.009)	(0.199)

These weights are for the calculations using two, four, and twenty six week lags, that is $k = 2, 4$, and 26. The weights are defined as the mean investment per stock in each portfolio as a fraction of the total dollar investment. The reader should realize that the various portfolios are shorthands for the strategies, thus $R > 0$ and $V > V_m$ indicates the portfolio of stocks for which the individual stock return was greater than zero and the individual volume was greater than market volume at $t - k$. The other portfolios are as discussed in section 4.3 of chapter 4. The $R > 0$ portfolio indicates the combined portfolio from the portfolios with positive return in period $t - k$. Similarly, the $R < 0$ portfolio indicates the combined portfolio from the portfolios with negative return in period $t-k$. The $V > V_m$ portfolio indicates the combined portfolio from the high volume stock portfolios in period $t-k$. Similarly, the $V < V_m$ portfolio indicates the combined portfolio from the low volume stock portfolios in period $t - k$. The standard errors are presented in parentheses. The sample consists of 1559 weeks.

Table 4.8: Mean Number of Stocks in Each Portfolio for All Four Strategies

Portfolio	$R>0$ $V>V_m$	$R>0$ $V<V_m$	$R<0$ $V>V_m$	$R<0$ $V<V_m$	$R>0$	$R<0$	$V>V_m$	$V<V_m$
Panel A: For All Strategies								
All Stocks	58	155	57	201	213	258	115	356
	(32)	(63)	(33)	(66)	(84)	(84)	(39)	(41)
Smallest	11	27	11	44	38	55	22	70
	(6)	(11)	(6)	(11)	(14)	(14)	(6)	(6)
Medium	11	32	11	39	43	51	23	71
	(7)	(14)	(7)	(15)	(18)	(18)	(9)	(10)
Largest	12	32	12	36	45	48	24	68
	(12)	(18)	(11)	(18)	(21)	(21)	(17)	(17)

These mean numbers are for the calculations using a one week lag, that is k=1. The numbers are similar for other lags, given that we use non-overlapping lags. The reader should realize that the various portfolios are shorthands for the strategies, thus $R > 0$ and $V > V_m$ indicates the portfolio of stocks for which the individual stock return was greater than zero and the individual volume was greater than market volume at $t-k$. The other portfolios are as discussed in section 4.3 of chapter 4. The $R > 0$ portfolio indicates the combined portfolio from the portfolios with positive return in period $t-k$. Similarly, the $R < 0$ portfolio indicates the combined portfolio from the portfolios with negative return in period $t-k$. The $V > V_m$ portfolio indicates the combined portfolio from the high volume stock portfolios in period $t-k$. Similarly, the $V < V_m$ portfolio indicates the combined portfolio from the low volume stock portfolios in period $t-k$. The standard errors are presented in parentheses. The sample consists of 1559 weeks. The mean numbers of stocks in each portfolio is independent of the weighting strategy given that positive or negative return and the volume lead are the ones that separate the portfolios. The mean number of stocks and standard deviations were rounded to the nearest integer.

Table 4.9: The Profits from Various Studies of Contrarian Strategies Using Different Weighting Schemes

Portfolio	Lehmann (1990) $u_{it}(k) = \frac{R_{it-k}-\bar{R}_{t-k}}{\sum(R_{it-k}-\bar{R}_{t-k})}$	Lo and MacKinley (1990) $u_{it}(k) = -\frac{1}{N}(R_{it-k} - R_{mt-k})$	Conrad et al. (1994) $u_{it}(k) = \frac{R_{it-k}}{\sum R_{it-k}}$	Chincarini/Llorente (1995) $u_{it}(k) = \frac{R_{it-k}}{\sum R_{it-k}}$
All Stocks	17.9	0.169	1.16	24.87
	(41.07)	(20.81)	(1.60)	(14.74)
Smallest	10.6	0.453	n.a.	40.73
	n.a.	(18.81)		(12.97)
Medium	2.1	0.106	n.a.	13.57
	n.a.	(13.84)		(10.08)
Largest	0.4	0.062	n.a.	9.81
	n.a.	(11.22)		(8.04)

These are all the profits from various strategies using a one week lag, that is $k = 1$. These portolios are all costless portfolios. The profits are multiplied by 1000. n.a. stands for not available.