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Stock Market Overreaction

A Test Based on Price and Volume Filters

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Abstract

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This thesis tests for an overreaction effect on the Stockholm stock exchange A-list using data for the period January 4 1982 through August 30 1999. The test is basically a replication of some parts of a test successfully employed by Cooper (Cooper, 1999) on the American stock markets NYSE and AMEX. The thesis also contains an overview of the theory and previous empirical findings on the overreaction effect.

The results indicate a small but statistically significant reversal of portfolios of the most extreme winners and losers. The results are not as unambiguous as those of Cooper's survey are. When using a first-order-price filter, the most extreme portfolios are significant and consistent with the overreaction effect. However, for the second-order-price and first-order-price-and-volume filter the results are difficult to interpret, and could have been caused by random perturbations. It would be difficult to trade successfully using these findings alone, if trading costs, such as the bid-ask spread and brokerage fees are taken into account.

We believe that the significant results that have been found are not caused by the bid-ask-bounce effect to any large extent. However, they could have been caused by a survivorship bias in the data. In addition, the results can be consistent with the efficient market hypothesis if the risk premium is allowed to be time varying.

Contents

Chapter 1

Introduction

This introductory chapter contains a concise background, the problem statement, purpose, result vision, target audience and the delimitations made. The chapter ends with a brief outline of the thesis.

1.1 Background

For over 30 years, the efficient market hypothesis (EMH) has remained the central proposition of financial economics. According to the EMH, stock prices are equal to their fundamental values given by the expected present value of the cash flows accruing to the stock. The cash flow expectations are assumed to be formed rationally, taking all available information into account.

In recent years, the traditional view that securities are rationally priced to reflect all publicly available information has been questioned, see (Daniel et al., 1998). The growing list of anomalies on the stock market with respect to the rational models has intensified the search for an alternative or complementary view on how stock prices are set.

Kahneman and Tversky (Kahneman and Tversky, 1982) in a study on experimental psychology found that people tend to overreact to dramatic and unexpected events. DeBondt and Thaler (DeBondt and Thaler, 1985) apply this result to the stock market and find that it is possible to earn an excess return by buying (selling) stocks that have done extremely poorly (good) in past years. During the 1990's, a short-term variant of the original long-term overreaction hypothesis has been given much attention.

In a recent study, Cooper (Cooper, 1999) tests the short-term overreaction hypothesis for large-capitalization securities on the NYSE and AMEX. He finds significant predictability of stock returns, and reports on a profitable simulated strategy using these previous findings.

Cooper uses a somewhat different method compared to previous short-term overreaction articles. One interesting aspect of Coopers method is that he, besides lagged returns, incorporates lagged volume into the portfolio formation rule. The method makes it possible to test what effect changes in trading volume has on the overreaction effect.

1.2 Problem Statement

The predictability of stock returns has been a question subject to heated debate for a long time. An implication of an overreaction effect is that stock returns might be negatively autocorrelated, which in turn suggests that stock prices might be predictable to some degree, see (Lo and MacKinlay, 1990). The predictability puts the validity of even the weakest form of the efficient market hypothesis in question.

The logic of the efficient market hypothesis is difficult to question. For example, how would it be possible for an abnormal return opportunity caused by overreaction to survive the process of arbitrage? The overreaction hypothesis is thus a problem for the advocates of the efficient market hypothesis, e.g., many economics researchers. The presence of a large overreaction effect is also interesting for practitioners on the financial market since an economically significant overreaction effect could make it possible for investors to make excess returns simply by studying historical stock returns.

Whether the stock market experiences a long-term overreaction effect is also of interest to firms planning the date of an equity issue. If the market is efficient, the timing decision becomes unimportant since efficiency implies that equity is always sold for its true value at any point in time, see (Ross et al., 1993, p. 355).

In addition, the overreaction effect is interesting because it represents a behavioral principle that may apply in many other contexts in finance. For example, according to DeBondt and Thaler (DeBondt and Thaler, 1985), investor overreaction possibly explains Schiller's earlier findings that when long-term interest rates are high relative to short rates, they tend to move down later. Consequently, the presence of an overreaction effect could be of interest to practitioners in a variety of different areas in finance.

The overreaction phenomenon raises questions that can be divided into four main categories

1. What is the definition of the term overreaction?

2. What are the implications of an overreaction effect to market efficiency?

3. What possible explanations are there to the overreaction effect?

4. How can investors exploit the overreaction effect to earn abnormal returns?

This is a quite useful structure since it provides a general picture of the complex overreaction problem.

1.3 Purpose

The main purpose is to investigate if evidence of short-term overreaction in Swedish stock prices can be found using Cooper's filter based portfolio-weighting method. The method also involves an analysis on what effect changes in trading volume has on the overreaction effect.

To enable an understanding of the results of the test, the thesis will also answer the four questions raised above. The attention is directed towards the question of short-term overreaction, but to complete the discussion, overreaction over other time horizons will also be described.

1.4 Result Vision

Several articles have been written on the short-term overreaction in the past. The methodologies used in these articles have been criticized on a number of accounts. Given the explanations offered by these articles, the empirical evidence in support of short-term overreaction is not convincing. Cooper develops several modifications to the methodologies used in past overreaction articles. By applying Cooper's method to the Swedish stock market, this thesis aims at getting a good estimation of the overreaction effect in Swedish stock prices, and to see if the method used by Cooper can be successfully applied to e.g., the Swedish stock market.

1.5 Delimitations

This thesis tests for a short-term overreaction effect in the surviving stocks of the Stockholm stock exchange A-list for the period January 4 1982 to August 30 1999. The study closely follows Coopers test. Trading costs are not taken into account, and there are no adjustments for dividends. The simulation (see section 3.9) performed by Cooper is not performed in this study.

1.6 Brief Outline

Chapter 2 describes the overall method of this thesis. Chapter 3 contains a description of relevant theory and earlier empirical findings. Section 3.9 describes Coopers method and gives a summary of his results. Chapter 4 contains a discussion of the data used in this thesis and a description of the method. Chapter 5 contains the results of the test. Chapter 6 gives an analysis of the results. Chapter 7 contains the summary and conclusions.

Chapter 2

Method

In this chapter, the overall method used in this thesis is discussed. A detailed description of the method and data used in the test for an overreaction effect is given in chapter 3 and 4.

2.1 Choice of Subject

Before starting to search for an interesting topic, we knew we wanted to do some sort of quantitative analysis on the Swedish stock market. To get some idea of what is currently being debated the search began by reading economic journals. As it turned out, the topic for the thesis was found in *The Review of Financial Studies*. The article of interest was the article "Filter Rules Based on Price and Volume in Individual Security Overreaction" by Michael Cooper (Cooper, 1999). Cooper uses an interesting method to test for an equally interesting phenomenon. This thesis is a replicate study of the major points of his study, using his method to test for short-term overreaction effects in Swedish stock prices.

2.2 Information Sources

Most of the books on financial markets that we have read devote little attention to the overreaction phenomenon. Overreaction is often mentioned in chapters on market efficiency as possible indications against market efficiency. The discussion is often brief and does not include an explanation on why it would exist. More thorough presentations of the overreaction effect were found in economic journals such as *Journal of Finance*, *The Review of Financial Studies*, and *Quarterly Review of Economics and Finance*, to mention a few.

After having browsed the most recently issued journals, a search for earlier relevant articles was performed. To find interesting articles the reference listings of some interesting articles were used. In addition, article database search engines such as *EBSCO* and *Econlit* were used. Some of the keywords used in these searches were: *overreaction*, *mean reversion*, *underreaction*, *momentum* and *contrarian*.

2.3 Source Criticism

The books referenced in this thesis are in general quite skeptical to the idea that the stock market would overreact. In the referenced articles, there is no consensus whether the stock market overreacts. In some articles, convincing evidence was found in favor of an overreaction effect, whereas in other articles convincing evidence against the overreaction effect was found. This thesis aims to give a nuanced description of the overreaction effect, but the reader should be aware that the description is based on a sample of articles. A different sample might give a somewhat different picture.

Chapter 3

Theory and Earlier Empirical Findings

This chapter discusses the theory and the empirical findings necessary to understand what an overreaction effect is, and what implications it might have for the efficient market hypothesis. In addition, account of different explanations to the overreaction effect is given. The delayed overreaction and possible explanations to the effect are discussed in the section that follows. The chapter ends with a discussion about trading rules used by practitioners to derive advantage from the overreaction effect.

3.1 Random Walk

In earlier theories, the *random walk* was synonymous to market efficiency, see for example (Ross et al., 1993, p. 338). Therefore, the discussion on market efficiency begins with a short description of the random walk.

Since the publication of Bachelier's thesis "Theory of speculation" in 1900 (Bachelier, 1900) in which he proposes that stocks follow a *random walk*, this has been a subject of considerable interest. In the past, several different definitions of the random walk have been proposed. According to the basic definition of a random walk, successive stock returns are assumed to be independent and identically distributed, see (Fama, 1970).

The assumption of independently distributed returns implies that the return in one period is of no use in predicting the return in the next. The assumption of identically distributed returns implies an assumption about the risk premium being constant. By risk premium is meant the compensation received for risk in terms of the systematic portion of stock return variance. The most common risk measure used in finance is the Capital Asset Pricing

Model (CAPM) beta. The CAPM beta is the regression coefficient of the stock return as a function of the return on the market index. In equilibrium, compensation should only be received for this systematic risk, see (DeBondt and Thaler, 1989).

The assumption of a constant risk premium constitutes a possible explanation for the high return earned by different trading strategies. This topic will therefore be covered in depth in the section covering time-varying risk premia.

According to Lo and MacKinlay (Lo and MacKinlay, 1990), empirical evidence shows that historical stock market prices do not follow random walks.

3.2 Stock Return Autocorrelation

In dealing with time-series data, where the returns follow a natural ordering in time, there is a possibility that the return at a point in time will be correlated to previous returns. If there is such a correlation in time, the time-series is said to be autocorrelated, see (Hill et al., 1997, p. 237).

Most trading strategies suggested in recent studies use stock-return autocorrelation to generate profits. This thesis tests the profitability of a trading strategy exploiting short-term negative serial dependence in asset returns, see (Lo and MacKinlay, 1990).

If serial correlation coefficients are significantly different from zero, the stock market does not follow a random walk.

3.3 Market Efficiency

How to define market efficiency has been a question of much controversy in the past. According to Fama (Fama, 1976, p. 133-143), an efficient capital market is a market that is efficient in processing information. The prices of securities observed at any time are based on a correct evaluation of all information available at that time. In an efficient market, prices therefore fully reflect available information. This is sometimes referred to as a *fair game model*, e.g., in (Fama, 1970). This implies that the market should adjust prices fully and instantaneously when new information becomes available.

Since some types of information are more readily available than others, the information can be separated into subgroups. The most common classification system uses three different subgroups: historical price, public and all information. The classification of information makes it possible to divide efficiency into three different degrees of efficiency: weak form, semi-strong form and strong form of market efficiency, see (Ross et al., 1993, p. 338).

A capital market is said to satisfy weak-form efficiency if it fully incorporates the information in past stock prices. If the market reflects all publicly known information it is semi-strong efficient and if it also incorporates private information such as insider information it is strong-form efficient. If a market is strong-form efficient it is also weak and semi-strong form efficient since it reflects all information, including historical and public information, see (Ross et al., 1993, p. 341).

If the market is efficient, even in its weakest form, trading strategies using past stock returns should not be able to generate risk-adjusted abnormal returns.

3.4 Overreaction Hypothesis

A stock market anomaly is an apparent departure from an efficient market that allows financial actors to make abnormal risk-adjusted returns. Some of the anomalies mentioned in the financial literature are the week-of-the-day effect, the small-firm effect, the ex-dividend effect, the January effect and the P/E-ratio effect, see (Claesson, 1987, p. 18). It is beyond the scope of this thesis to explain the details of all these anomalies, but since some of them have been proposed to explain the overreaction phenomenon, some will be discussed later.

As mentioned earlier, a stock market is efficient if the prices fully reflect all available information. For this to occur, investors must behave rationally, see (Hull, 1993, p. 191). If the investors behave irrationally and do not utilize the available information, stock prices will not be the most efficient estimate of the present value of future firm cash flows, see (Elton and Gruber, 1995, p. 437-438). If this is the case, investor competition will fail to eliminate profitable trading opportunities.

Empirical stock market research in the past three decades has presented a body of evidence with systematic patterns that are not easy to explain with rational asset pricing models, since the rationality has been proven to be consistently violated, see (DeBondt, 1994).

Financial economics is, perhaps, the sub-discipline of economics where actual human behavior is taken into account the least. Finance literature reveals little interest in investor decision processes or in the quality of investor judgement. It has not always been this been this way. Earlier generations of economists such as Irving Fisher, John Maynard Keynes and Benjamin Graham put greater emphasis on the imperfect nature of human decision-making. In modern finance, we simply insist that, whatever people do, they do it right, see (DeBondt, 1994).

In a study on experimental psychology, Kahneman and Tversky (Kahneman and Tversky, 1982), referenced in Iwan and van der Put (Iwan et al., 1997), find that people tend to overreact to unexpected and dramatic news events. In several studies DeBondt and Thaler (DeBondt and Thaler, 1985) and (DeBondt and Thaler, 1989) investigates whether this applies to the financial market. DeBondt and Thaler were the first to empirically test the overreaction hypothesis, but the idea of an overreaction effect was mentioned by Keynes in "The general Theory" in 1936, see (DeBondt, 1991). In their empirical studies, DeBondt and Thaler find indications of an overreaction effect implying that investors are not rational.

The overreaction hypothesis claims that the predictability found in stock returns is due to investor overreaction that temporarily moves the stock prices away from their fundamental values. Eventually, however, the prices are corrected as actual future events predictably turn out to be either less rosy or more pleasant than originally estimated, see (DeBondt, 1991). DeBondt and Thaler (DeBondt and Thaler, 1985) proposes the following two hypotheses: "(1) Extreme movements in stock prices will be followed by subsequent price movements in the opposite direction. (2) The more extreme the initial price movement the greater will the subsequent adjustment be". To be able to focus on extreme price movements, many of the earlier articles on the overreaction effect examine returns following one-day price declines of ten percent or more (see e.g., (Bremer and Sweeney, 1991), (Cox and Peterson, 1994), and (Park, 1995)).

The early work on overreaction discussed long-term overreaction. However, during the last ten years, much attention has also been given to short-term overreaction in stock prices (see e.g., (DeBondt and Thaler, 1989), (Jagadeesh, 1990), (Lehmann, 1990) and (Lo and MacKinlay, 1990)).

The test in this thesis, described in detail in chapter four, tests for short-term overreaction in that it uses a return-horizon of one week after the portfolio formation date. Weekly and even monthly return horizons are considered short term. It is important to distinguish between short-term and long-term overreaction since it is now generally accepted that short-term fluctuations in stock returns differ in many ways from three to five-year returns, see (Lo and MacKinlay, 1990).

If stock prices systematically overshoot, then their reversal should be predictable from past return data alone, see (DeBondt and Thaler, 1985). The existence of an overreaction effect implies that a strategy of buying losers and selling winners will earn a positive expected return because the losers (winners) are likely to become future winners (losers), see (Conrad et al., 1997). This strategy is called a contrarian strategy and will be discussed further in section 3.8 later in this chapter.

The reported profitability of several contrarian strategies has led many to conclude that stock markets overreact, see (Lo and MacKinlay, 1990). If an overreaction effect is found, it could be interpreted as an indication against weak-form market efficiency since it makes it possible to profit from a strategy using past information only.

Possible Explanations to the Overreaction Effect

Several studies have shown the presence of overreaction in the stock market and the empirical evidence is substantial. The interpretation of these apparently anomalous results is less clear and according to recent studies, there are several possible explanations for the overreaction phenomenon found in earlier empirical studies, see (Richards, 1997). Virtually all models of overreaction imply that the abnormal returns are due to negative autocorrelation in the return of individual stocks, see (Lo and MacKinlay, 1990). However, there are a number of alternative explanations.

The presentation of the possible explanations below forms the basis for the evaluation of the method used in this thesis.

The explanations proposed in earlier studies can be categorized as follows:

- Time-varying risk premium
- Micro-structural problems
- Economic insignificance
- Other market imperfections or anomalies
- Stock market liquidity
- Methodological explanations
- Other real but unknown economic explanations
- Other psychological explanations

Time-Varying Risk Premium

Both the random walk hypothesis and the weak-form market efficiency hypothesis claim that future returns should not be predictable using historical price data. However, some definitions of the random walk are more restrictive than the efficient market hypothesis since they assume that stock returns are identically distributed through time, see (Ross et al., 1993, p. 338). This is probably not true since the risk of different companies can change over time because of changes in their structure and line of products etc, see (Claesson, 1987, p. 57).

This implies that even though evidence of a random walk means that the market is weak-form efficient, the reverse does not hold due to for example the possibility of a time-varying risk premia.

Stock returns being non-random can be interpreted in two ways, according to Fama (Fama, 1976, p. 143):

1. Expected returns are constant and the *fair game model* as mentioned earlier can be rejected, with the implication that weak-form market efficiency can be rejected.

2. Expected returns are time varying, with the implication that weak-form market efficiency cannot be rejected.

This means that if a pattern is found in the stock returns, weak-form efficiency cannot be rejected unless the assumption of a constant risk premium is valid.

Higher Systematic Risk

A common explanation to the overreaction effect in losers found in empirical studies is that the firms selected are risky rather than undervalued. If the firms are extra risky, they should carry an extra risk premium, implying that their return could be normal even tough evidence suggesting an overreaction is found. This is possible if the risk premium can be assumed time varying.

DeBondt and Thaler found that traditional risk measures such as the capital asset pricing model betas were unable to explain the overreaction effect in their study since the betas had not changed on average after the extremely low/high return date, see (DeBondt, 1994). In their study on long-term overreaction effects (DeBondt and Thaler, 1985), they found that the average betas of the securities in the winner portfolios are significantly larger than the betas of the loser portfolios. This means that loser portfolios not only outperform the winner portfolios, but also that if the CAPM is correct, the loser portfolios are also significantly less risky.

DeBondt and Thaler argue that while traditional risk measures seem unable to explain the overreaction effect, risk may yet be an important part of the story since it may be essential to distinguish between true objective risk and perceived risk. If investors are reluctant to hold a certain stock because it is perceived as being more risky and not enough rational traders are willing to step in, then perceived risk and true risk have a similar effect on stock prices, see (DeBondt, 1994).

In contrast to DeBondt and Thaler's findings, other studies have found that in some cases the contrarian strategy has been shown to generate insignificant abnormal returns after adjusting for the time-varying systematic risk for the winner and loser stocks (see e.g., (Chan, 1988), (Ball and Kothari, 1989) and (Chen and Sauer, 1997)).

According to Lehmann (Lehmann, 1990), it is possible to determine whether predictability in stock returns could be explained by a time-varying risk premium or an overreaction effect by examining returns over short intervals. He argues that over short intervals the risk premium should be constant since systematic short-run changes in fundamental values should be negligible in an efficient market with unpredictable arrival of information. This is assumed to hold even if there are predictable variations in expected security returns over longer horizons. Under these assumptions he rejects the efficient market hypothesis since he finds arbitrage opportunities using a short-term trading strategy where he buys past losers and goes short in past winners.

Richards (Richards, 1997) finds no evidence that test-period returns of prior losers were significantly riskier than those of prior winners, either in terms of their standard deviations or other risk factors.

Micro-structural Explanations

Micro-structural problems could be a problem for studies on short-term overreaction since these studies are often transaction intensive and based on short-term price movements. According to Jagadeesh and Titman (Jagadeesh and Titman, 1993), negative autocorrelation found in these studies may reflect the presence of short-term price pressure or a lack of liquidity in the market rather than overreaction. However, the short-term price pressure might also serve as an explanation to the overreaction effect. Low liquidity gives rise to micro-structural problems such as the bid-ask bounce and cross-autocovariance across securities.

Short-Term Price Pressure

One of the most important characteristics investors look for in an organized financial market is liquidity since it determines the ability to buy or sell significant quantities of security quickly with relatively little price impact, see (Campbell and Lo, 1997, p. 99-100).

If the market is strictly efficient, investors should be able to sell as many shares as they desire without depressing the stock price, see (Ross et al., 1993, p. 356). If this assumption does not hold and the sale of large blocks of stocks can temporarily depress the price, it could generate test results in favor of an overreaction effect since the stock price will eventually revert to its true value.

Bid-Ask-Bounce

One important source of measurement error when calculating stock returns is the bid-ask spread. Conrad, Gultekin and Kaul (Conrad et al., 1997) show that most, but not all, of the earnings from price reversals they find in their study on the NYSE/AMEX sample may not be a reflection of overreaction but may instead be generated by the bid-ask bounce effect. They argue that in the presence of measurement errors caused by the bid-ask spread, calculated returns will be negatively autocorrelated at least at lag 1, even if "true" returns are serially uncorrelated, see (Conrad et al., 1997).

The logic behind the bid-ask explanation can more easily be understood by considering the bid-ask bounce on a transaction-to-transaction basis. Assume that a stock quote is 49 bid and 50 ask, and that the last trade was made at 49. Suppose a market purchase order is placed. Then the order is executed at 50. If it is followed by a market sell order, the price will decline to 49. Thus, an increase will be followed by a decrease, and a reversal has occurred, see (Elton and Gruber, 1995, p. 423). As random buys and sells arrive at the market, prices can bounce back and forth between bid and ask prices, creating serial correlation in the return, even if the economic value of the security is unchanged, see (Campbell and Lo, 1997, p. 99).

According to Cox and Peterson (Cox and Peterson, 1994), large one-day price declines are likely to be associated with substantial selling pressure, increasing the probability that a closing transaction is at a bid price and, in turn, leading to a reversal the next day due to the bid-ask bounce effect. They also argue that if the bid-ask bounce is not an important factor, and instead short-term overreaction is the cause for large one-day reversals, then the greater the one-day decline, the greater the subsequent reversal should be. If the bid-ask bounce is the main source for the overreaction effect, larger initial declines should not lead to greater subsequent reversals. The logic behind this conclusion is that larger declines are not likely to have larger problems with the bid-ask bounce than smaller declines.

Jagadeesh and Titman (Jagadeesh and Titman, 1993) also provide evidence on the relation between short-term return reversals and bid-ask spreads that supports the bid-ask bounce explanation.

In Coopers study, a skip-day procedure was used to correct for the bid-ask bounce. The methodology, first suggested by Lehmann (Lehmann, 1990) has been criticized by Conrad, Gultekin and Kaul (Conrad et al., 1997). They argue that Lehmann's procedure can lead to deceptive conclusions about price reversals. Instead of the skip-day procedure, they suggest the use of a bid-bid procedure. When using the bid-bid procedure the bid-quotations are used instead of the close-quotations that are used in the skip-day procedure.

Conrad, Gultekin and Kaul (Conrad et al., 1997) show that evidence of reversals on large-capitalization stocks is less affected by bid-ask bounce problems than is reversal evidence on small capitalization stocks. Similar results have been reported by, for example, Richards (Richards, 1997) who conclude that micro-structural problems get smaller when stock market turnover increases since the liquidity in stocks increases and the bid-ask bounce gets smaller.

Cross-Autocovariance Across Securities

As mentioned earlier, one implication of stock market overreaction is positive expected return from a contrarian investment rule. The apparent profitability of several contrarian strategies has led many to conclude that stock markets do indeed overreact, see (Lo and MacKinlay, 1990).

Lo and MacKinlay (Lo and MacKinlay, 1990) reports that daily returns of individual securities are slightly negatively autocorrelated and that portfolio returns are strongly positively autocorrelated. According to them, this somewhat paradoxical result can mean only one thing: large positive correlations across individual securities across time. They question if the profitability of contrarian strategies is due to overreaction effects. They explain the positive profits by cross-autocovariance across securities. To see how, consider the following example where the market is assumed to consist of only two stocks.

"If, for example, a high return for security A today implies that security B's return will probably be high tomorrow, then a contrarian investment strategy will be profitable even if each security's return are unforecastable using past returns of that security alone" (Lo and MacKinlay, 1990).

Lo and MacKinlay assume that when stock A's return is higher than the market, the contrarian investor will sell A and buy B and as a consequence of the cross-autocovariance among the stocks make a positive profit on stock B. Because of cross-autocovariance a contrarian investment rule could earn positive expected returns even though each security's return is serially independent. Lo and MacKinnlay report that less than 50 percent of the expected return is due to an overreaction effect.

One source of cross-autocorrelation is what has come to be known as the *nonsyncronous trading* or *nontrading* problem, in which prices of distinct securities are mistakenly assumed to be sampled simultaneously. If some stocks are traded less frequently than others, news that affects those stocks traded more frequently could influence the returns of thinly traded securities with a lag. As an example, assume that stock A is traded less frequently than B. If news that affect the aggregate stock market arrives at the end of the day, it is more likely that B's end-of-day price reflects this information than A's, simply because A may not trade after the news arrives. The fact that A adjusts with a lag compared to B causes cross-autocorrelation between the daily returns of A and B, see (Campbell and Lo, 1997, p. 84).

Lo and MacKinlay refer to this as a *lead-lag relationship* and report that the returns of large capitalization stocks almost always lead those of smaller stocks.

Economic Insignificance

It is also possible to consider the market as efficient with respect to information if it is impossible to make economic profits by trading based on this information. According to this definition of market efficiency, evidence of risk adjusted abnormal returns does not imply that the market is inefficient as long as the inefficiency is too small for investors to be able to trade it away because of trading costs and costs of information, see (Cooper, 1999).

For example, according to Conrad, Gultekin and Kaul (Conrad et al., 1997), trading costs of 0.20 percent eliminates all of the overreaction profits they find in their NYSE/AMEX sample.

Seen from this perspective, market efficiency could have improved in recent years since Internet trading has lowered trading costs for some types of investors. However, this does not need to be the case for all investors since institutional investors have paid low commissions for a long time. This is an interesting issue, but it is beyond the scope of this thesis to discuss it further.

According to Keim and Madhavan (Keim and Madhavan, 1997), the impact of high trading costs is less likely to affect large capitalization stocks. In their definition of trading costs, they include relative spreads and price pressure effects, which are likely to be smaller for large capitalization stocks.

Another related problem is that tests that are performed on a large sample could generate statistically significant results even if the inefficiency is relatively small. However, inefficiency is of interest only if it is economically significant, see (Claesson, 1987, p. 36).

Other Market Imperfections or Anomalies

It has been argued that much of the overreaction effect found in earlier studies can be explained by other market imperfections such as the size effect, the P/E-ratio effect, the day-of-the-week effect and the January effect. It has been shown in a number of studies that different anomalies are often strongly related.

Banz (Banz, 1981) published one of the first articles on the size effect in stock returns. Banz showed that excess returns would have been earned over the period 1936-1977 by holding small firms. An interesting aspect of his result is that size had roughly the same statistical significance in explaining returns as the CAPM's beta, see also (Elton and Gruber, 1995, p. 423-425).

According to Cox and Peterson (Cox and Peterson, 1994), the size effect and stock price reversals are also linked to the liquidity in the market. They argue that if temporary liquidity plays an import role, reversals should be stronger in less liquid markets and smaller firms should experience stronger reversals than larger firms should. In their study, they find that smaller firms experience larger reversals than large firms do and conclude that market liquidity is an important factor in the reversal process. According to Cooper (Cooper, 1999), the reason for this could be that a larger percentage of their profitability could be attributable to a lead-lag effect and to higher transaction costs.

Richards (Richards, 1997) reports that there is evidence that winner-loser reversals are larger among the smaller markets than the larger ones. He finds the largest reversals for two small markets, the Norwegian and the Danish markets, with differentials of 23.5 and 16.8 percent per annum, respectively. He also finds that the largest market, the American, also demonstrates substantial reversals of 8.3 percent per annum. (Sweden was also included in his study but the result is not reported in his article).

Richards refers to his findings as a *small country effect* that could be related to some form of market imperfection, or to greater differences in risk. He argues that because of the fact that smaller markets experience larger reversals, there is less justification for a claim that the reversals represent an anomaly.

Banz (Banz, 1981) argues that the P/E-ratio anomaly is really masquerading for a size effect since stocks of small companies tend to have low price-earnings ratios. There is less information known about small firms, and thus investors are likely to be less confident about their estimates of both risk and expected return. This may increase the return required to invest in the stock since the lack of confidence in the estimates of the small companies adds an element of risk. It can also be argued that it costs more to buy shares of smaller firms because the market is thinner and thereby causes the bid-ask spread to be greater, see (Haugen, 1997, p. 694-696). If the stock market for some reason demands a higher return to hold smaller firms, the size effect itself is not inconsistent with market efficiency.

According to Elton and Gruber (Elton and Gruber, 1995, p. 437-438), stock market *losers* should be expected to consist of more small firms, partly because they are losers, than the *winners* category. According to Zarowin (Zarowin, 1990), the overreaction phenomenon is just another manifestation of the size effect since the reversals he found disappears after controlling for size.

One explanation for the long-term overreaction phenomenon frequently mentioned in previous articles is the January effect. A large number of studies have shown that stock market return is larger in January than in other months, see (Claesson, 1987, p. 129). A substantial part of the size effect occurs in January, implying that the size effect and the January effect are strongly related, see (Elton and Gruber, 1995, p. 423-425).

The significant difference in expected percentage change for stocks depending on what day of week trading is conducted is often referred to as a day-of-the-week effect. A large number of studies have found that average stock returns are lower on Mondays than other days of the week, see (Claesson, 1987, p. 108). This is a possible source of error for tests on short-term overreaction.

Baytas and Cakici (Baytas and Cakici, 1999) find evidence in favor of long-term overreaction in all countries they study, with the notable exception of the US. However, they find that price-based arbitrage portfolios outperform those based on size or past performance. They therefore conclude that, in these countries, the overreaction might be a price-based phenomenon.

Other market imperfections that could affect the results when testing for overreaction are stock market reactions to events such as the announcement of earnings, dividends and stock splits. Since these announcements occur rather seldom, it is however not likely that they influence the results to a large extent.

Stock Market Liquidity

Many of the explanations discussed so far may depend on stock market liquidity in one way or the other. It is likely that lack of liquidity could give rise to price pressure effects and micro-structural problems, such as the bid-ask bounce and cross-correlation across securities caused by non-synchronous trading.

Over the last ten years, the trading volume has increased substantially at the Stockholm stock exchange. The large increase in trading volume can be seen in figure 3.1. The data is taken from (Stockholm Stock Exchange, 1999).

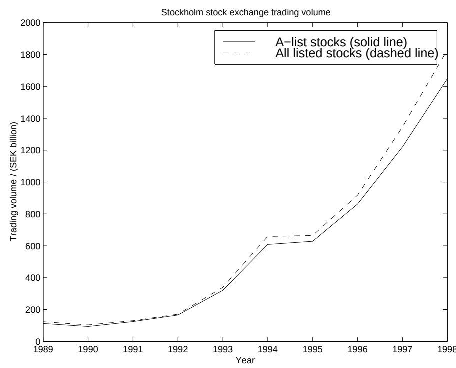

Figure 3.1: The increase in trading volume on the Stockholm stock exchange

Since micro-structural problems should decrease with larger trading volumes, these problems should be smaller for the more recent years in the period used in the test for overreaction.

Methodological Explanations

It has been argued that the overreaction effect found in empirical studies may be the result of methodological errors. In this section, some of the most frequent flaws are discussed.

Arithmetic Method when Calculating Returns

According to Dissanaike (Dissanaike, 1994) the arithmetic method, which is often used in overreaction studies to calculate cumulative stock returns is flawed. Dissanaike argues that the arithmetic method of computing multi-period returns from single period returns is unsatisfying since it implies arithmetic averaging across securities where the portfolio is rebalanced to equal weights each month. It is unrealistic because monthly returns are simply added together instead of being multiplied and therefore bear little relation to the returns that would actually accrue to an investor.

To see this, consider a stock that displays consecutive monthly prices of 100, 50 and 80. If the returns were added, the return would be equal to $-0.5 + 0.6 = 0.1 = 10\%$, whereas a geometric method would yield an accumulated return of $(0.5 \cdot 1.6) - 1 = -0.2 = -20\%$. In his study, Disanaike provides empirical evidence that the arithmetic method could yield biased results in studies on overreaction. In contrast, Baytas and Cakici (Baytas and Cakici, 1999) use a geometric method and still find evidence of overreaction.

Data Snooping and Data Mining

Stock return data is now widely available, data power is cheap and financial theories are often well specified, allowing them to be tested. This has led many academics and practitioners to perform a variety of empirical tests on the overreaction effect and it is therefore difficult to assess the significance of an individual study. If an empirical test is viewed as a single test, standard statistical theory indicates that the probability of observing a t-statistic of, for example, at least as large as 3.07 is, given some parameters, less than 0.11 percent. If we instead acknowledge the fact that it is likely that other tests have been carried out over the same time-period that were perhaps not successful and hence perhaps not reported, the probability changes. If the number of tests is 100, the probability that the test with the highest t-statistic is above 3.07 is about 10 percent. With 650 tests, this probability is close to 50 percent, see (Jagadeesh and Titman, 1999). Data mining is the process of performing a large number of tests, and only reporting the ones that turned out to be significant or in support of the examiners preconceived ideas.

Data snooping is the activity of looking at the data later used in a test, before the test is designed. If the examiner looks at the data and finds an, in his opinion, interesting pattern, he might be led to design a test to try to find evidence of that pattern in the data. However, the result of this test will be seriously flawed, and the normal statistical techniques will give misleading results. They will perhaps be correct for the studied period, but will be very difficult to generalize. If he wants to generalize using the dependencies he saw in the data, he must use an entirely different set of data to run the test, than the data used to design the test.

However, it is not always easy to get two sufficiently large independent sets of data. If one is tempted to use the same data for both tasks, one must be aware of the danger of data snooping. One situation that is probably quite common, is that one researcher, that has looked at the data, say from time a to time b, suggests a test for future research. Then another researcher decides to perform that test, but he may not realize that the other researcher has looked at the data from a to b, and perhaps performs his test using data from a to c, where $c \geq b$. The traditional statistical techniques will not work as expected in this case, and may indicate significant results when there are none, except perhaps for that particular set of data. The solution is to use an independent set of data, perhaps from another country, that no one influencing the test design has looked at in advance.

In some situations, the problem of data snooping is less relevant. This is the case, for example if it is possible to easily generate huge amounts of data, or if the data has so little noise that there is no need to use statistical techniques. This is also the case if one is only interested in the properties of the data that are actually tested and does not intend to make any general conclusions.

Survivorship Bias

According to Haugen the most conspicuous flaw in previous studies on contrarian strategies is the method by which the sample of firms is chosen. Typically, a number of firms are chosen, all of which have survived the entire period of the study. By not including those *loser* companies that indeed go into bankruptcy after having performed badly on the stock market, a potential problem with a trading rule investing in such companies is eliminated, causing a bias in favor of the trading rule, see (Haugen, 1997, p. 694-696). Selecting stocks ex Ante instead of ex Post, which is quite common, could avoid this type of sample bias.

Companies that go into bankruptcy may first follow a downward trend of declining stock price, before disappearing from the stock market when they go into bankruptcy. Other companies that experience the effects of a public offer may increase in value over a long period before they are delisted. These types of stocks will be excluded from any test that uses survivors only. The excluded stocks are of the type that if they start to move in one direction, they are likely to continue to move in that direction. If some of these trend-following stocks are excluded from the survey, we will have a problem. If there is initially an equilibrium between trend-following stocks and reverting stocks, and some of the trend-following stocks are removed, it will probably be easier to find evidence of a reversion effect for the remaining stocks. However, this evidence would be useless in practice, i.e., for trading, because it is not known in advance which stocks will be the future survivors.

Another effect of the survivorship bias is that the mean return may change when some stocks are excluded. For example, if we were to compare the return of a portfolio of survivors to the return of the stock market index, there would probably be a discrepancy. Whether this difference is positive or negative is not obvious. However, by comparing to the return of an alternative index of survivors, this part of the survivorship bias can be mitigated.

Other Real but Unknown Economic Explanation

Inefficiencies in stock markets could persist after they have been discovered if they are too small to be exploited. The explanation could also be that the regularities are not inefficiencies and exist because of economic reasons, see (Claesson, 1987, p. 207). According to Claesson (Claesson, 1989), an anomaly is a simple regularity among stock returns with the implication that return size can be explained by some other factor than risk.

To be able to determine what is an abnormally high (or low) return, you need to set up a model for how the market determines what a normal return is. The return that the model predicts is then compared to the realized return. This means that the test is a test of the model that is used and the conclusions only hold under the assumption that the model is correct, see (Claesson, 1987, p. 4).

Any test for market efficiency must first assume an equilibrium model that defines normal security returns. If efficiency is rejected it could be because the market is truly inefficient or because an incorrect equilibrium model has been assumed. The implication of this is that market efficiency as such is very difficult to reject, see (Campbell and Lo, 1997, p. 24).

If the economic explanation is not a compensation for risk as it is defined by rational models, such as the capital asset pricing model (CAPM), the high return earned by contrarian strategies could continue to exist in an efficient stock market if they are compensation for some other priced factor than this risk, see (Claesson, 1989).

According to DeBondt and Thaler (DeBondt and Thaler, 1985), most explanations for the well-known P/E-effect are usually based on an alleged misspecification of the CAPM. Some explaining factors are said to have been left out, and if these unknown factors where included in the "correct" equilibrium valuation model the anomaly would disappear. The problem is that unless these unknown factors can be identified, the hypothesis is un-testable. Time will tell if a multifactor model that incorporates these unknown factors can be constructed.

Other Psychological Explanations

Above explanations have been presented that could explain the overreaction effect found in many empirical tests. The discussion started with explanations that are rational in nature such as risk, methodological explanations, and micro-structural explanations. Then the overreaction as a symptom of other anomalies was discussed, and last there was a discussion covering other real but unknown economic explanations, which could be used as the last re-

Term	Portfolio formation period	Portfolio holding period
Short-term	1 week to 1 month	1 week to 1 month
Medium-term	3 to 12 months	3 to 12 months
Long-term	3 to 5 years	3 to 5 years

Table 3.1: The definitions of the different terms used in this thesis

sort for advocates of the efficient market hypothesis. If human behavior is taken into account and the fact that human decision-making might not always be perfectly rational is acknowledged, some psychological explanations come to light.

As mentioned earlier the overreaction hypothesis is a psychologically inspired alternative to rational asset pricing models, but other explanations on how investors behave have also been discussed in economic journals.

A general criticism often raised by economists against psychological theories is that the number of possible irrational behavior patterns that could be used as explanations is unrestricted. Thus, it is often claimed that allowing for irrationality opens a Pandora's box of ad hoc stories. A good psychological finance theory must therefore be grounded on psychological evidence on how people actually behave (such as the overreaction hypothesis), see (Daniel et al., 1998).

The next section discusses delayed overreaction effects and in the section *Possible Explanations to the Delayed Overreaction Effect* on page 29, some psychologically inspired explanations are discussed, such as overconfidence, biased self attribution and fads or fashions. Although the explanations are often discussed in the context of delayed overreaction, it is believed that they to some extent could be used as explanations to short-term overreaction as well.

3.5 Delayed Overreaction Effects

This far, negative autocorrelation over short periods (one week to one month) and over long periods (three to five years) has been discussed. In this section, positive autocorrelation for periods between three and 12 months is discussed. This is sometimes referred to as short-term, but here it is referred to as medium-term to avoid confusion with time periods of one week to one month, which is sometimes also referred to as short-term in earlier empirical studies. See table 3.1 for an overview of these terms.

The portfolio formation period is the period during which the stock must have performed in a certain way to be included in a specific portfolio. The holding period is the period during which the performance of the stocks in the portfolio is measured.

Jagadeesh and Titman (Jagadeesh and Titman, 1993) report on a trading strategy of buying stocks that have performed well in the past and selling stocks that have performed poorly in the past 3 to 12 months, that generate significant positive returns over a 3 to 12 month holding period. The profitability implies that stock returns are positively autocorrelated over a certain period.

Just as for the results found in tests for overreaction, the source of the return and the interpretation of the evidence are widely debated. While some have argued that the result provides evidence of market inefficiency, others argue that it is a compensation for risk, or the product of data mining.

Since similar results have been found on a variety of stock markets and in different time-periods, see (Daniel et al., 1998), it is not unreasonable to assume that stock returns are positively autocorrelated in the medium-term. The list of possible explanations is long and not all of them will be discussed here. Note that the positive and the negative autocorrelation do not need to be contradictory to each other because of the differences in the time-horizons.

If the positive autocorrelation exists because investors underreact to information, the predictability in stock returns would disappear once the information is fully incorporated in stock prices. This interpretation suggests that post-holding-period excess returns will be zero, see (Jagadeesh and Titman, 1999). Jagadeesh and Titman (Jagadeesh and Titman, 1993) report that more than half of the excess return generated by their portfolio disappears within the following two years. Since this implies a negative autocorrelation, they conclude that the positive autocorrelation they find in the medium term is not due to an underreaction to information, but rather to a delayed overreaction, see (Jagadeesh and Titman, 1999).

In a similar fashion Daniel, Hirshleifer and Subrahmanyam (Daniel et al., 1998) show that positive return autocorrelations can be a result of "continuing overreaction" which is followed by long-run correction. Thus, medium term positive autocorrelation can be consistent with long-run negative autocorrelation.

DeBondt and Thaler (DeBondt and Thaler, 1985) and Richards (Richards, 1997) also found positive autocorrelation for winners in the medium term and negative autocorrelation in the long term.

Frennberg and Hansson (Frennberg and Hansson, 1993) have studied the Swedish stock market between the years 1919 and 1990. In their study, they found strong evidence of positively autocorrelated returns for investment horizons of one to 12 months and indications of negative autocorrelation over horizons of two years or more. In the study, monthly returns of a value-weighted stock market index including all stocks on the main list of the Stockholm stock exchange was used.

Even though the results are interesting, they should not necessarily be taken as indications of positive autocorrelation in individual stock returns because of the possibility of cross autocorrelation in stock returns. This could be one reason for the positive autocorrelation in stock returns they found over such short investment horizons as one month. If the cross-autocorrelation is strong enough, the positive index autocorrelation could be compatible with a negative autocorrelation in individual stock returns.

Possible Explanations to the Delayed Overreaction Effect

This section briefly presents some explanations on why the stock market could overreact in the medium-term.

Overconfidence

Perhaps the most robust finding in the psychology of judgement is that people are overconfident and therefore overestimate their abilities. For example, a well-known finding is that 90 percent of the automobile drivers in Sweden consider themselves "above average". The overconfidence leads people to overestimate the reliability of their knowledge and reasoning, see (DeBondt, 1994).

Daniel, Hirshleifer and Subrahmanyam (Daniel et al., 1998) suggest that traders attribute the performance of ex-post winners to their stock picking skills and the performance of ex-post losers to bad luck. This phenomenon is called *biased self-attribution*. As a result, these investors become overconfident about their ability to pick winners and thereby overestimate the precision of their positive signals for these stocks. Based on their increased confidence in their positive signals they push the prices of the winners up above their fundamental values. The delayed overreaction that this causes will eventually lead to negative autocorrelation in the stock prices as they revert to their fundamental values, see (Jagadeesh and Titman, 1999).

Fads or Fashions

An obvious fact of life is that people are influenced by one another. DeBondt (DeBondt, 1994) argue that fads or fashions are as likely to emerge in financial markets as anywhere else. This could cause stocks that are in fashion to temporarily move away from their fundamental values. However, as the fashion changes, the prices of the stocks that go out of fashion will decrease. A related issue often mentioned in financial press is *sector rotation*, which refers to the idea of the stock market interest moving from one sector to another.

Rational Speculative Bubbles

According to the theory of rational speculative bubbles, investors are aware of the fact that stock market prices sometimes exceed their fundamental values. The excess return earned by staying in the market compensates for the risk of the bubble bursting and stocks reverting to their fundamental value. Thus, the actors need not necessarily be irrational, see (McQueen and Thorley, 1991).

Trading Strategies

Investors who, for example, buy past winners and sell past losers could move prices away from their fundamental values temporarily and thereby cause a delayed overreaction in stock prices, see (Jagadeesh and Titman, 1993).

An important difference between fads or trading strategies and rational bubbles is that fads or trading strategies can cause reversion in stocks that are either overvalued or undervalued, whereas reversion from rational bubbles can occur only when prices exceed their true value.

3.6 Asymmetry in the Overreaction Effect

Cooper finds that the overreaction effect is asymmetric in his test, larger for losers than for winners. Similar result have been found by Baytas and Cakici (Baytas and Cakici, 1999), who found that losers outperform the market to a greater extent than winners underperform the market in six of the seven countries they studied. The fact that short positions generally are less profitable than long positions has also been documented by Bremer and Sweeney (Bremer and Sweeney, 1991) and Cox and Peterson (Cox and Peterson, 1994).

Possible Explanations to the Asymmetry in the Overreaction Effect

A few explanations to the asymmetry have been discussed in other studies. DeBondt and Thaler (DeBondt and Thaler, 1985) mention differences in systematic risk as a possible explanation. In their study they find that the average betas of the winner portfolios are significantly larger than the betas of the loser portfolios. According to DeBondt and Thaler the high risk in the winner portfolio could lead to a weaker reversal effect for winner portfolios, since the high stock price is the result of the high risk-premium required by the market because of the large systematic risk, rather than an overreaction.

DeBondt and Thaler propose an explanation for asymmetry in long-term overreaction effects. In the light of the results found by Cooper, it is possible that the same explanation can be used for asymmetry in short-term overreaction effects as well. Cooper found that the winner portfolios have larger betas than the loser portfolios. He calculates CAPM betas for price-only portfolios and reports betas of 0.94 for the winner portfolios and 0.58 for the loser portfolios.

DeBondt and Thaler (DeBondt and Thaler, 1989) also give an alternative, but related explanation where there is assumed to be a difference between perceived risk and actual risk. The risk of both extreme winners and extreme losers are assumed to be perceived as being very risky. For example, losers might be considered very risky since the risk of bankruptcy may be overestimated and winners since they appear to have so much downside potential. Such firms will bear an excess risk premium.

A reversal effect will be expected for losers since the excess risk premium and the overreaction effect both work in the same direction of lowering prices. For winners, the overreaction effect drives the prices too high while the excess risk premium holds the prices down. Since the two effects go in opposite directions, the reversals of winners should be smaller or nonexistent.

The fact that winner stocks experience smaller reversals than loser stocks could also be due to the existence of cross autocorrelation. According to Lo and MacKinlay (Lo and MacKinlay, 1990), the cross effects are generally positive in sign. If this is true, cross-autocorrelation will strengthen the reversal effect for loser portfolios, and impair it for winner portfolios.

3.7 The Role of Volume

Campbell, Grossman and Wang (Campbell et al., 1993) give an explanation of how relative daily stock market volume could be used to figure out whether large one day price changes will be reversed. They assume that there are two different types of investors: non-informational investors who desire to sell stock for exogenous reasons, and risk-averse utility maximizers who are willing to accommodate the selling pressure if they are rewarded in the form of lower stock prices so that they receive a higher expected return. In a sense, these investors could be thought of as market makers. If stock prices fall it could be due to public information that has caused all investors to reduce their valuation of the stock market, or it could be due to exogenous selling pressure caused by non-informational traders.

If public information has arrived, there is no reason to expect a high volume of trade, whereas selling pressure caused by non-informational traders must reveal itself in unusually high volume. When this kind of market makers buy the stocks that the non-informational traders supply the market with, the stock price will be temporarily depressed, and it is therefore likely that the stock price will go up the next day. Thus, the model suggests that price changes accompanied with high volume will tend to be reversed and that it is less true of price changes on days with low volume.

Wang (Wang, 1994) suggests an opposite view on how volume could be used to explain the existence of reversals. He assumes that there are two different types of investors, agents who posses private information and those who do not. Wang hypothesizes that when investors with private information trade, high future returns are expected when increases in stock prices are accompanied with high trading volume. If Wang's hypothesis is correct, a relatively large trading volume on the portfolio formation date should lead to smaller reversals or maybe even positive autocorrelation, see (Cooper, 1999).

3.8 Trading Strategies

This section describes different trading strategies that have been proposed as alternatives to a simple buy and hold strategy.

Contrarian Strategies

The terms *contrary thinking* or *contrarian investing* were first popularized by Humphrey Neill in 1954, who in turn credits William Stanley Jevons with the concept. Jevons stated in his *Primer of Political Economy* that "in making investments it is foolish to do just what other people are doing, because there (sic!) almost sure to be to many people doing the same thing", see (DeBondt, 1994).

At least since the publication of Graham and Dodd's (1934) "Security analysis", there have been a school of investors who follow value-based investment strategies, suggesting that buying stocks out-of-favor and holding them for the long term would generate abnormal stock returns. Stocks considered being out-of-favor could for example be those with low ratios of market to book value, low P/E ratios or low past returns, see (DeBondt, 1994).

Overreaction Strategies

An overreaction strategy is a contrarian strategy taking advantage of the overreaction effect to produce an abnormal return. An investor using a short-time overreaction strategy exploits negative autocorrelation over short time horizons (one week to one month) by going long in prior stock market losers and short in stock market winners, see (Lo and MacKinlay, 1990).

A long-term overreaction strategy is similar to the short-term with the difference that it exploits negative autocorrelation over long time horizons (3 to 5 years). A long-term overreaction strategy is similar to a value strategy in the sense that both invest in stocks with relatively low past returns. An obvious difference between the two is that most value strategies say nothing about going short in stock market winners.

Momentum Strategies

An investor using a momentum strategy invests in stocks that have had a relatively high increase in price in the recent past, see (Jagadeesh and Titman, 1993). A momentum strategy is basically a trend following strategy. The idea behind a momentum strategy is that if a security has outperformed the market, it is likely to continue to do so. The financial press often refers to momentum investors as investors who buy whatever is currently "hot", see (Richards, 1997).

Cooper uses filters to decide what stocks are likely to create abnormal returns. In earlier studies, a filter is sometimes defined in a way that is not entirely consistent with the way Cooper uses filters. To avoid confusion, this thesis will refer to the earlier filter rules as traditional filter rules. The traditional filter rule was first proposed by S. Alexander, see (Elton and Gruber, 1975, p. 55). The traditional filter rule is similar to the momentum-strategy trading-rule in that they both benefit from positive autocorrelation. Alexander suggests the following filter trading rule, see (Fama, 1976, p. 140):

"If the price of a security moves up at least y percent, buy and hold the security until its price moves down at least y percent from a subsequent high, at which time simultaneously sell and go short. The short position is maintained until the price rises at least y percent above a subsequent low, at which time one covers the short position and goes long".

Grinblatt and Titman (Grinblatt and Titman, 1989) show that some mutual funds using a momentum strategy have earned abnormal positive returns. According to Jagadeesh and Titman (Jagadeesh and Titman, 1993) the positive returns earned by practitioners using a momentum-strategy trading rule, such as the mutual funds, do not have to be incompatible with the overreaction hypothesis since the two are often using different time horizons. Contrarian strategies often use very short-term (1 week to 1 month) or very long-term return reversals (3 to 5 years), while momentum strategy practitioners base their selections on price movements over the past 3 to 12 months.

Momentum strategies could at first glance appear to be the exact opposite of contrarian strategies since they profit from positive autocorrelation while contrarian strategies profit from negative autocorrelation. In the light of the discussion on delayed overreaction, it could well be that they in fact profit from the same phenomenon, namely the overreaction effect, but using different time-horizons.

3.9 Cooper's Test

This section will describe the procedure used by Cooper (Cooper, 1999) in his test for stock market overreaction.

Data

Cooper uses daily data for the period 1962-1993. At the beginning of every year, the 300 largest companies listed on the NYSE and AMEX are included in the survey. In using these large capitalization stocks, Cooper hopes to reduce the effect of lead-lag effects and various other liquidity problems. In addition, the average bid-ask spread is expected to be smaller when using large capitalization stocks.

Definitions

The stock return r_{t-1} for week $t-1$ is calculated using the standard formula $r_{t-1} = \frac{p_t}{p_{t-1}} - 1$, where p_t is the price of the stock on Wednesday in week t.

Stocks are classified as *loser-price* in week t if they have had a negative return in week $t-1$, and as *winner-price* if they have had a nonnegative returns in week $t-1$. A stock having two consecutive weeks, $t-2$ and $t-1$, of negative returns of approximately the same size is classified as *loser-loser-price* in week $t-1$, and a stock with two consecutive weeks, $t-2$ and $t-1$, of nonnegative returns of approximately the same size is said to be *winner-winner-price* in week $t-1$.

The relative change in volume, ρ_{v_t}, for a stock in week t is calculated as

$$\rho_{v_t} = \frac{\frac{V_t}{S_t} - \frac{V_{t-1}}{S_{t-1}}}{\frac{V_{t-1}}{S_{t-1}}} = \frac{\frac{V_t}{S_t}}{\frac{V_{t-1}}{S_{t-1}}} - 1,$$

where S_t is the number of outstanding shares in week t and V_t is the share turnover in week t. By adjusting for the number of outstanding shares, the effect of splits and equity issues is probably reduced. Note that V_t is the number of stocks traded during the week t, and not the value of the stocks traded.

A stock having a positive growth in volume in week $t-1$ is said to be *high-volume*, and a stock having a negative growth in volume in week $t-1$ is said to be *low-volume*.

Portfolio Formation Rules

A stock is included in a particular portfolio based on the stock's magnitude of return during the previous week, the two previous weeks, or on a combination of the previous week return and the growth in volume during the last week compared to the week before. To avoid problems with non-trading days, only stocks having 10 consecutive days of strictly positive volume are included in the sample for each week.

First-Order Price Filter

Stocks are filtered into one of 12 different first-order-price filter portfolios using the first-order-price filters specified below.

Loser

$$\begin{aligned} -k \cdot a > r_{i,t-1} &\geq -(k+1) \cdot a, \qquad && k = 0,1,2,3,4 \\ -k \cdot a > r_{i,t-1}&, && k = 5. \end{aligned}$$

Winner

$$\begin{aligned} k \cdot a \leq r_{i,t-1} &< (k+1) \cdot a, \qquad && k = 0,1,2,3,4 \\ k \cdot a < r_{i,t-1}&, && k = 5. \end{aligned}$$

Here, $r_{i,t}$ is the return for stock i in week t, k is a filter portfolio counter, and a is the width of the portfolios, see figure 3.2.

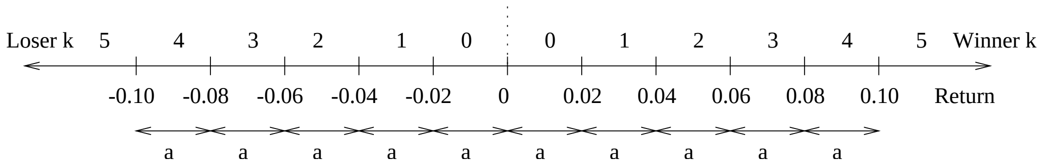

Figure 3.2: The first order price filter

Second-Order Price Filter

Stocks that happen to be categorized into the *same* first-order-price-filter portfolio for two consecutive weeks are categorized into the corresponding portfolio, i.e., the one with the same filter counter, also for the second-order-price filter. If instead a stock is in one portfolio the first week $t-2$ and in another portfolio the next week $t-1$, the stock does not end up in any second-order-price-filter portfolio at all. The second-order-price-filter portfolios containing stocks being *winners* for two consecutive weeks are denoted *winner, winner price* portfolios with a filter counter k. Second-order-price-filter portfolios containing stocks being *losers* for two consecutive weeks are denoted *loser, loser price* portfolios with a filter counter k.

For example, if a stock gains 3.5% in week $t-2$ it is, according to the above first-order-price filter, said to be in portfolio *winner price* $k=1$ in week $t-2$. Then if it gains 3.6% in week $t-1$ it is said to be in portfolio *winner price* $k=1$ in week $t-1$ as well. Since it ends up in the same portfolio for two consecutive weeks, it is also said to be in the second-order-filter portfolio *winner, winner price,* $k=1$ for week $t-1$. Now, if the stock gains 1.5% in week t it is said to be in portfolio *winner price* $k=0$ in week t. By being classified into different portfolios for the weeks $t-1$ and t, the stock will not end up in any second-order-price-filter portfolio at all for week t. We feel that this way unfortunately a large part of the scarce data is lost.

First-Order Volume Filter:

The volume filter is of first order only. Stocks are categorized as having positive or negative growth in volume, and to different degrees, according to the value of the relative growth in volume, $\rho_{v_{i,t}}$:

Negative

$$
\begin{aligned}
&-l \cdot b > \rho_{v_{i,t-1}} \geq -(l+1)\cdot b, && l = 0,1,2,3,4 \\
&-l \cdot b > \rho_{v_{i,t-1}}, && l = 5.
\end{aligned}
$$

Positive

$$\begin{aligned} l \cdot c \leq \rho_{v_{i,t-1}} &< (l+1) \cdot c, && l = 0,1,2,3,4 \\ l \cdot c &< \rho_{v_{i,t-1}}, && l = 5. \end{aligned}$$

b is the width of the negative growth portfolios, c is the width of the positive growth portfolios and l is a filter category counter. b is set by Cooper to be 15%, and c is 50%, see figure 3.3. The reason for having differently spaced portfolio limits for the positive and negative growth-in-volume portfolios is the fact that the range of the relative-growth-in-volume is not symmetric, with the interval of possible values being $]-1, \infty[$, in combination with a wish for spreading the stocks reasonably well among the available portfolios. Note that no stock will ever have a growth in volume that is less than -1, and any stock having a growth in volume of exactly -1 is automatically excluded from this survey due to its liquidity problem. In combining both the first-order-price filter and the first-order-volume filter in classifying stocks, $12 \cdot 12 = 144$ first-order-price-and-volume-filter portfolios are formed each week.

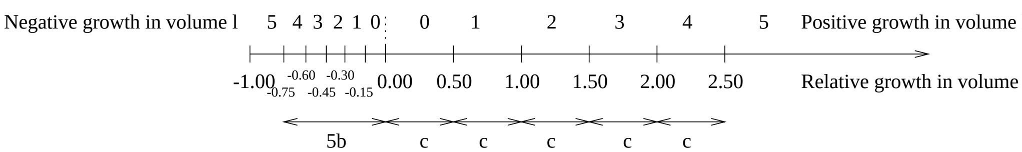

Figure 3.3: The first order volume filter

Portfolio Evaluation

All the stocks in a portfolio in one week have equal weight in the portfolio, so that the portfolios can be said to be equally weighted. Each portfolio is held for one week and then liquidated. Then the portfolio return is calculated for that week. After all the weeks have been processed, the average return of each portfolio is calculated for those weeks that the portfolio holds an equity position. The average portfolio returns are tested against zero using a t-test.

The reason for testing against zero instead of a market index is to avoid causing an apparent reversal effect due to fear of the positive index autocorrelation, which in turn is caused by the cross-autocorrelation among individual stocks. Cooper in fact also tests the average portfolio returns against the mean returns of all sample stocks, but the difference in the results is said to be small.

By skipping the last day in the portfolio formation period, i.e., the last Wednesday, so that the portfolio formation week consists of the four trading days, i.e., from the Wednesday close to the Tuesday close, Cooper hopes to reduce the effect of bid-ask bounce. The portfolios formed this way are called skip-day portfolios. The same procedures and calculations as for the full-week portfolios are repeated for the skip-day portfolios.

Result Summary

Cooper reports results consistent with a contrarian view. A portfolio of stocks having performed badly in one week is likely to be a winner in the next week and vice versa. The magnitude of the previous returns also affects the magnitude of the future returns. A large positive (negative) return in one week is on average followed by a large negative (positive) return in the next week. Most of the portfolio returns are found significantly different from zero, with the winner portfolios on average being somewhat less significant and having a somewhat smaller magnitude than the loser portfolios. Although the differences in magnitudes and significance levels between losers and winners are small, they are statistically significant.

Cooper also reports statistically significant differences between the mean portfolio returns of the full-week portfolios and the skip-day portfolios. However, the general trends and patterns still appear to be roughly the same for the skip-day portfolios as those for the full-week portfolios.

Portfolios of stocks with two consecutive weeks of changes of similar sizes are generally reported to have larger reversals than the single week price-filter portfolios. I.e., loser-loser-price portfolios experience larger gains than loser-price portfolios, whereas winner-winner-price portfolios have larger losses than winner-price portfolios.

For portfolios formed using both the first-order-price and the first-order-volume filter, Cooper finds a greater forecasting ability than for the first-order-price filter on its own. Reversals are generally found greater in magnitude if there was a preceding decrease in volume during the portfolio formation week. Portfolios of stocks experiencing a growth in volume during the portfolio formation period have a lot smaller reversals and some even display positive autocorrelation.

Cooper then goes on to perform a simulation to test if his findings can actually be used without knowing the full period outcome in advance. The simulation starts in 1977, when the imaginary investor bases his investment decisions on past data only. One week passes and the outcome of the investor's portfolio is evaluated. Then the procedure is repeated for this new point in time. The result of this simulation indicates that the use of the filter strategies is highly profitable and significantly better than a passive benchmark portfolio. Note however that the costs associated with trading, such as the bid-ask spread and brokerage fees are set to zero.

Cooper also performs some calculations based on the data to check some minor issues that are not absolutely necessary for this thesis. Due to the limited time available, neither these calculations nor the simulation will be performed in this thesis.

Chapter 4

Empirical Test

One intention of this thesis is to present a replication of the major points of the Cooper (Cooper, 1999) study using data from the Swedish stock market. This chapter will give details on the data and method used in this study, as well as any deviations from the study of Cooper.

4.1 Data

The data consists of the companies currently listed on the Swedish Stockholm stock exchange A-list, 93 companies. For companies with multiple lines of stocks listed, the line with the highest liquidity was selected. The available information is open, close, high and low trades, and the traded volume, on each trading day. The data is taken from the Delphi Economics stock analysis program *Vikingen börs 4.01*, that is supplied with data for the time January 4 1982 through August 30 1999. Vikingen contains data only on those stocks that are currently listed on the Stockholm stock exchange. This means that stocks that are no longer listed have been excluded from the test. There is thus a survivorship bias in the data. In addition, data on merged companies is available only since after their merger. An example of this is Astra that merged with Zeneca to form AstraZeneca. Data on AstraZeneca is available from April 6 1999, whereas there is no data at all on Astra before the merger. The data is adjusted for splits, but not for dividends.

The data is exported from Vikingen to Excel, where it is rearranged and then saved as text files. These text files are then read into a program written in Delphi, that performs all the calculations. Delphi is a programming language from Borland Inc. similar to Pascal. There is no link between Delphi and Delphi Economics whatsoever. The Delphi program, specifically written for this thesis, first checks if the dates are valid for all stocks. The data from the Vikingen program contains some errors that the Delphi program attempts to remove. If a valid trading date is missing from the data on one company, the program inserts the date as though there was no trading of the company's stock on that date. The Vikingen data sometimes contains trading data on non-trading days. This data is sometimes simply a copy of the immediately preceding trading day data, and is easily identified as being erroneous. Data on non-trading days is deleted by the Delphi program.

The program that was specifically written for this thesis might contain errors that influence the result. Due to the limited time available, the program was written as a quick hack for use in this thesis only. It is not intended to be maintained after having served its purpose. It might not be easy to understand and does not follow good coding standard. It is however available via e-mail on request to *f94ts@efd.lth.se* for the interested reader.

4.2 Calculation of Return and Change in Volume

There are two slightly different ways to calculate returns used in this thesis. The difference arises from when the return is calculated and how missing data is handled.

To calculate returns used for categorization and filtering, we know all the data in advance. The data has been collected before it is needed to calculate the return at the portfolio formation date. A week starts at the Wednesday close in week $t-1$, and continues to the next week, t, Wednesday close. If one of the Wednesdays is not a valid trading day, if for example the market was closed that day, there is no data on the Wednesday close. Then the week starts at the opening trade of the next available trading day of the same week instead. If the Wednesday is a valid trading day but there is still no data on the close because there was no trade of the company's stock, no attempt is made to calculate that stocks return for that particular week, and the week return is declared invalid. The week return is also declared invalid if on any of the valid trading days of the week there was no trading. This way some stocks that might experience liquidity problems due to noncontinuous trading are excluded from the survey for that week. If all the necessary data is available, the return is calculated as $r_t = \frac{c_t}{c_{t-1}} - 1$, where r_t is the return in week t and c_t is the Wednesday close in week t.

The volume is the sum of the value of the trading on the days between the close quotes used for the return calculation. For example, assume that the return of week t was calculated from the Wednesday close week $t-$

1 to the next week t Wednesday close. Then the volume for that week t would be the sum of the volume for Thursday and Friday of week $t-1$, and Monday, Tuesday and Wednesday of week t. The relative change in volume is calculated as $\rho_{v_t} = \frac{v_t}{v_{t-1}} - 1$, where v_t is the volume of week t and ρ_{v_t} is the relative change in volume between week $t-1$ and t. Cooper does this slightly different in that he calculates the change using the number of traded stocks adjusted for changes in the total number of stocks. This difference is caused by the availability of data, and will probably not affect the result to a significant extent. If on any one of the trading days of the week there is no trading, so that the close is undefined and the volume is zero for that day, the week is declared as invalid. An attempt is still made to calculate the volume v_t for this week however, since the week volume is needed in the calculation of the next week's relative change in volume.

An alternative way to calculate return is used when investing in a stock. To calculate the return from investing in a stock, the outcome will not be known in advance. Hence, there is no way to tell all the days that will turn out to be missing from the future data. A return period starts at the Wednesday close of week t and continues to the week $t+1$ Wednesday close. If the Wednesday of week t is not a valid trading day, the next valid trading day is used. If the Wednesday close for week $t+1$ is missing for some reason, the next available open is used instead.

4.3 Discretization and Categorization

The calculated data of weekly stock return and volume change is discretized and the stocks are categorized into different portfolios.

First-Order Price Filter:

Loser

$$\begin{aligned} (k+1)\cdot a > r_{i,t-1} \geq k\cdot a, \qquad & k = -1,-2,-3,-4,-5 \\ (k+1)\cdot a > r_{i,t-1}, \qquad & k = -6. \end{aligned}$$

Winner

$$\begin{aligned} k\cdot a \leq r_{i,t-1} < (k+1)\cdot a, \qquad & k = 0,1,2,3,4 \\ k\cdot a < r_{i,t-1}, \qquad & k = 5. \end{aligned}$$

Here, $r_{i,t}$ is the return for stock i in week t, k is a filter portfolio counter, and a is the width of the portfolios, see figure 4.1. a is set to be 2%, similar to Coopers selection. Note that the filter counter k has been renumbered for the loser portfolios as compared to the Cooper study.

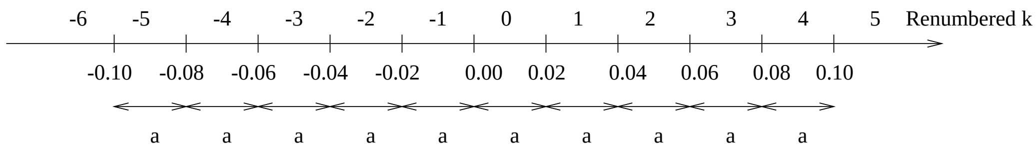

Figure 4.1: The first order price filter

Second-Order Price Filter:

A stock that ends up in the same first-order-price-filter portfolio for two consecutive weeks is also included in the corresponding second-order-price-filter portfolio. Stocks ending up in two different first-order-price-filter portfolios are not included in any of the second-order-price-filter portfolios for the later of the two weeks.

First-Order Volume Filter:

The volume categories are first order only. Stocks are categorized as having positive or negative growth in volume, and to different degrees, as follows:

Negative

$$\begin{aligned} (l+1)\cdot b > \rho_{v_{i,t-1}} \geq l\cdot b, &\qquad l = -1,-2,-3,-4,-5 \\ (l+1)\cdot b > \rho_{v_{i,t-1}}, &\qquad l = -6. \end{aligned}$$

Positive

$$\begin{aligned} l\cdot c \leq \rho_{v_{i,t-1}} < (l+1)\cdot c, &\qquad l = 0,1,2,3,4 \\ l\cdot c < \rho_{v_{i,t-1}}, &\qquad l = 5. \end{aligned}$$

b is the width of the negative categories, c is the width of the positive categories and l is a filter portfolio counter. b is set by Cooper to be 15%, and c is 50%. Note that the numbering of the filter portfolio counters is different with that used by Cooper, see figure 4.2.

The first-order-volume filter is combined with the first-order-price filter, giving a total of 144 first-order-price-and-volume filter portfolios.

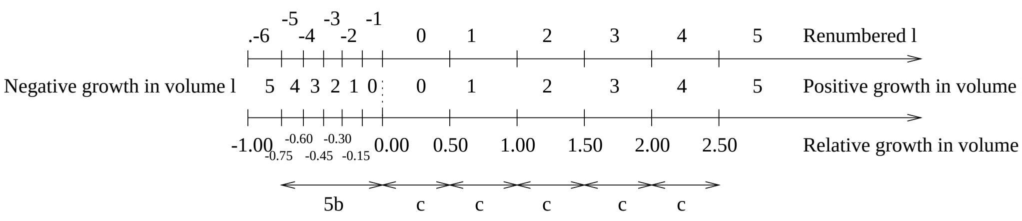

Figure 4.2: The first order volume filter with the renumbering of l

4.4 Portfolio Formation

The stocks are placed in their respective portfolio for each week. The stocks in a portfolio form an equally weighted portfolio that is held for one week. The portfolio is then liquidated. The average portfolio return is calculated for those periods in which the portfolio is not empty.

Benchmark Portfolios

For each of the above types of filtering (i.e. first-order price, second-order price, first-order price and volume), a corresponding benchmark portfolio is created. There is thus one benchmark for the first-order-price filter, one for the second-order-price filter and one for the first-order-price-volume filter. In every week, each stock satisfying the filter requirements is added to its respective filter portfolio as well as to the filter type's benchmark portfolio for that week. The benchmark portfolio is held for one week, liquidated and then the portfolio return is calculated, just as the other portfolios. The average benchmark portfolio return is calculated as the mean return of those weeks in which the portfolio is not empty.

Excess Return

To adjust the result of the filter portfolios, the appropriate benchmark portfolio mean return is deducted from the mean portfolio returns of the filter strategies. This will adjust the position of zero excess return to make it easier and more economically meaningful to try to see any reversal or other type of effect. However, since the average benchmark portfolio return is an uncertain value that must be estimated from the data, the uncertainty of these excess-return results will be larger. Still, the interpretation of these excess returns and significance levels should be easier and more economically interesting than the absolute returns obtained by comparing to zero absolute return.

The excess return of a filter strategy portfolio is calculated as $r_f - r_b$, where r_f is the return of a filter strategy portfolio, and r_b is the return of the strategy's corresponding benchmark portfolio. The standard deviation of this estimate of excess return is calculated as

$$\sqrt{\frac{s_f^2}{n_f} + \frac{s_b^2}{n_b}},$$

where s_f is the standard deviation of the return of the filter strategy portfolio, n_f is the number of observations of the filter strategy portfolio, s_b is the standard deviation of the return of the benchmark and n_b is the number of observations of the benchmark. Evidently the uncertainty of the excess return is higher than that of the absolute return unless the variance of the benchmark return is zero. Since a stock passing a filter can be included in only one of several filter portfolios, but is always added to the benchmark portfolio, the benchmark portfolio will contain stocks for at least as many weeks as the filter portfolio, i.e., $n_b \geq n_f$.

Chapter 5

Result

This chapter will present the result and highlight some interesting issues.

5.1 Available Data

The amount of available valid data is not constant over time. Due to survivorship bias, the fact that the number of companies listed on the Stockholm stock exchange A-list has increased during the studied period, and the increasing liquidity of the stock market, there is a trend of an increasing density of usable data. Figure A.1 illustrates the number of valid-trading-week stock data per month over the entire period. One valid-trading-week stock data is the same as that there is one week of valid data on one stock. The graph shows an increase in the density of available data, with a clear change around 1993. The curve seems to be very noisy. Part of this noise is caused by the fact that it shows aggregate data per month. However, the data is sampled once per week, normally Wednesday, and some months contain four Wednesdays whereas others contain five. Note also that the density of available data appears to decrease at the end of the period. The cause of this decline is unknown.

Since the density of available data is higher at the end of the period, the results below will be biased in favor of the later part of the period. Thus, if the overreaction effect is time varying, this study will unintentionally put a greater emphasis on the most recent period.

5.2 Benchmark Portfolios

The benchmark portfolios contain all the stocks that were filtered using their respective filter rule in each week. Table 5.1 lists the mean portfolio return

Benchmark	Mean/%	Std. dev./%	N
First-order price	0.383	3.05	778
Second-order price	0.377	3.95	700
First-order price and volume	0.380	3.16	732

Table 5.1: The benchmark portfolios

per week (Mean/%), the standard deviation of the portfolio returns (Std. Dev./%) and the number of weeks N that the benchmark portfolios contained stocks.

The mean returns are about the same for all three benchmarks. The 0.38% per week return is equivalent to $1.0038^{52} - 1 \approx 22\%$ per annum. The number of observations is lower for the second-order-price filter than for the first-order-price filter. This is reasonable in that a stock is less likely to pass the second-order-price filter. In addition, both the second-order-price filter and the first-order-price-volume filter require more data to be available than the first-order-price filter.

5.3 Price Filters

The results of the first and second-order-price filters is shown in table A.1 (loser-price and loser-loser-price) and A.2 (winner-price and winner-winner-price). The tables also show data for the skip-day portfolios.

First-order-price filters

For the loser-price strategies, we see an increase in mean portfolio return as the filter counter decreases. Four of the six portfolio returns are significantly above zero. For the winner-price strategies, we believe the mean return decreases as the filter counter increases. The returns for the three lowest filter levels are significantly above zero. The first-order-price filter result is plotted in figure A.2. There does not appear to be any trend in the middle part of the diagram. For the extreme loser-price portfolios, the mean return appears to increase, and for the extreme winner-price portfolios, the mean return appears to decrease.

The pattern of the returns of the skip-day first-order-price filter portfolios is similar to the full-week first-order-price portfolio returns. The portfolio returns significantly different from zero are -4 through 1, and thus excludes the previously significant -6 and -5. The number of observations in the extreme portfolios has decreased compared to the full week portfolios. This can at least in part be explained by the fact that the calculation period of the return used for filtering is one day shorter for the skip-day portfolios.

Second-order-price filters

The second-order-price filters put higher restrictions on which stocks are included in a portfolio. Thus, the number of observations is much lower than for the first-order-price filters. The mean returns of the full-week second-order-price-filter portfolios are plotted in figure A.3.

There is no general trend, but the curve appears to turn up (down) at the extreme loser (winner) end. The return for portfolios 0, 1 and 2 are significantly above zero, whereas the other portfolios are only insignificantly different from zero. The general pattern for the skip-day portfolios is similar.

Benchmark Comparison

The result of the price-filter strategies compared to the benchmark portfolios can be found in the appendix, see section A.3. The returns of the benchmark portfolios are subtracted from the respective filter-strategy portfolios. By subtracting the same number from all portfolios of a particular filter strategy, we do not expect any change in the patterns, but a translation of the zero return level. For the first-order-price filter, we get significantly positive excess return for the extreme loser portfolio (-6) and significantly negative excess return for the extreme winner portfolio (5), and thus there is at least some reversal effect. For the second-order-price filter, the only significant excess return is the negative return of the extreme winner portfolio.

5.4 First Order Price and Volume Filter

Tables of the result of the price-and-volume filters can be found in the appendix, see tables A.5 through A.12. Figure A.6 shows the mean returns of the price-and-volume filter portfolios, and figure A.7 shows the mean excess returns. The scale of the volume filter counter is blank in the figure, but the volume filter counter is supposed to start at $k = -6$ to the left and end at $k = 5$ to the right. By inspection of the plots, it is difficult to see any obvious large-scale trend. However, the plot might hint to a slight overweight of negative excess return values at the front of the diagram and a slight overweight of positive values at the back. A statistical test of this has not been performed.

Absolute Returns

Of all the 144 portfolio mean returns, only a few turned out to be significantly different from zero. The significant portfolios are (volume filter counter, price filter counter): (-5, -4), (-5, -2), (-3, -1), (-2, 0), (-3, 1), (-4, 3), (-2, 5), (0, -1), (1, 0), (5, 0), (0, 1), (1, 1), (5, 1), (1, 2), (5, 2), (3, 3), (4, 3), (5, 3), (3, 4). Thus, 19 portfolios have mean return significantly different from zero, and of those, 11 portfolios are winner-price positive-growth-in-volume portfolios. In looking at the number of observations for each portfolio, we see that the extreme portfolios have very few observations. This is due in part to the fact that 93 stocks are spread across 144 portfolios.

Excess Returns

Of the 144 portfolio mean excess returns, only eight are significantly different from zero excess return. This is around the number expected to be significant just by random perturbation at the 95% confidence level. Of the loser-price negative-growth-in-volume portfolios, there is one significantly positive return and one significantly negative return. Of the loser-price positive-growth-in-volume portfolios, there is one significantly negative portfolio only. Of the winner-price negative-growth-in-volume portfolios, all three significant values are negative. Of the winner-price positive-growth-in-volume, all three significant values are positive.

Chapter 6

Analysis

In this chapter the results presented in the previous chapter are analyzed. The results are compared to those found by Cooper and possible explanations to the results are discussed.

The return figures reported in the previous chapter are for a positive investment. Hence, reversals in the loser (winner) portfolios appear as positive (negative) returns. When a return is said to be statistically significant, it is significant at the five percent significance level if not otherwise stated.

The portfolio returns are generally close to zero with low levels of significance. The results do not look as nice as those presented by Cooper. There are several possible causes for this. First, our study uses less data and stocks with lower liquidity. The overreaction effect, or whatever causes an apparent overreaction effect, could be weaker on the Stockholm stock exchange than on the NYSE/AMEX. The overreaction effect could also have been stronger in earlier periods but identified by investors or otherwise reduced due to increasing market efficiency. There are some weak signs of an overreaction left, however.

6.1 First-Order Price Strategies

The analysis starts with the results for the first-order price strategies:

1. Loser-price, a strategy of buying last week's losers based on five-day week $t-1$ returns.

2. Winner-price, a strategy of buying last week's winners based on five-day week $t-1$ returns.

The results from the skip-day method will be discussed in a separate section later in the chapter.

Analysis of the Results for Different Filter Levels

According to DeBondt and Thaler, individuals tend to overreact to a greater degree when confronted with a larger information shock. In accordance with their hypothesis, we find larger reversals for the more extreme price filters. Four of the six loser-price portfolios generate statistically significant returns, whereas no significant reversal effect is found for the winner portfolios, as they also have a positive return at most filter levels. However, the positive returns for the winner portfolios do not necessarily contradict DeBondt and Thaler's theory since the positive returns are less significant for the more extreme filters, and even negative for the two most extreme filter levels.

These results are consistent with earlier findings in the sense that the reversal effect, if it is there, could be asymmetric. In the light of the discussion in chapter 3 on possible explanations to the asymmetry, the significantly positive returns to some of the winner portfolios do not necessarily indicate the absence of an overreaction effect for the winner portfolios. Instead, the significantly positive return of the winner portfolios could be caused by a general upward trend of the stock market as a whole, or at least of the stock market survivors.

In chapter 3 was mentioned that if the bid-ask bounce is the main source of the overreaction effect, large declines should not lead to greater subsequent reversals. The fact that we find larger reversals for the more extreme price filters could be taken as an indication that the bid-ask bounce is not the main source of the reversals found in the test.

6.2 Second-Order Price Strategies

This section contains an analysis of the results for the second-order price strategies:

1. Loser, loser-price, a strategy of investing in stocks that have incurred two consecutive weeks of losses, based on five-day returns in weeks $t-1$ and $t-2$.

2. Winner, winner-price, a strategy of investing in stocks that incurred two consecutive weeks of high returns, based on five-day returns in weeks $t-1$ and $t-2$.

By examining the result of the second-order price-filters, we try to see if some of the information contained in a longer sequence of security price provides extra information in predicting subsequent price changes.

Loser, Loser-Price

In Coopers study, the results from the loser, loser-price portfolios are generally larger than the returns to their one-week counterparts, the loser-price portfolios. Cooper finds a pattern of larger reversals for the two-week strategies relative to the one-week strategies, and the difference increases as filters become more extreme.

In our study the loser, loser-price portfolios earn smaller positive returns relative to their one-week counterpart. Half of the portfolios even have negative returns and the positive returns are statistically insignificant for the remaining portfolios. We find no evidence that the more extreme filter-levels, with equally large declines in price for two consecutive weeks, are followed by a larger reversal effect than the less extreme filters-levels.

Winner, Winner-Price

In contrast to the results from his loser, loser-price portfolios, Cooper finds no indications that the winner, winner-price portfolios should experience larger reversals than its one week counterparts. He also reports that, relative to its one-week counterpart, the reversals for the two-week strategies do not get larger as filters become more extreme.

Our results for the winner, winner-price portfolios are similar to those of Cooper in the sense that they also generate positive returns at many of the filter levels. Our results also indicate that the reversal effect does not appear to be larger for the two-week strategies than it is for its one-week counterpart. A difference from Cooper's results is that the positive returns generated by our winner-winner-price portfolios are larger rather than smaller at most of the filter levels, compared to the positive returns generated by the winner-price strategies.

Does Second-Order Price Filter Provide Extra Information?

Cooper suggests that by examining longer sequence of security price changes, it should be easier to predict subsequent price changes. The justification of this conclusion is, he claims, that his results imply that loser stocks are somewhat more likely to experience greater reversals if they have incurred two consecutive weeks of losses. He draws this conclusion even though the chi-square statistics testing for a significant difference in mean returns across the first and second-order filters are significant in only three of the six loser versus loser, loser comparisons, and never significant in the winner versus winner, winner comparisons.

In our test, even weaker evidence of a reversal effect is found when using second-order filters instead of first-order filters. Smaller positive returns are found for the loser portfolios, and larger positive returns for the winner portfolios, compared to the first-order filter. It seems as though the second-order-price filter suggested by Cooper does not help significantly in predicting subsequent price changes for our data set.

6.3 Results from the Skip-Day Method

To get some indication about the extent that the results might be attributable to the bid-ask bounce effect a skip-day method has been used. If the returns of the skip-day portfolios are not different from the returns generated by the portfolios formed conditioning on a five-day return period, this could be taken as another indication that the bid-ask bounce effect is not a large contributor to the reversal effect.

First-Order Skip-Day Portfolios

For the loser-price portfolios, lower returns are found at the two most extreme filter levels when using a skip-day method. The t-statistics for those portfolios are no longer significant. In contrast, there appears to be a pattern of larger and more significant returns at the four less extreme filter levels -4 through -1.

For the winner-price portfolios, there is a pattern of lower returns for the skip-day portfolios. The only exception is the most extreme filter level that generates less negative returns than its counterpart conditioned on a five-day portfolio formation period.

We find no evidence that the skip-day portfolios would experience large decreases in reversals compared to the strategies that use a five-day conditioning period. We actually find indications of larger reversals for some of the skip-day portfolios.

The result for the second-order skip-day portfolio is inconclusive. This is partially due to the very few observations of some of the portfolios.

Since this inconsistent pattern is difficult to interpret, the use of the skip-day method provides no information on how the bid-ask bounce affects the portfolio returns. These findings are similar to those of Cooper. He finds only a few significant Chi-square statistics when he tests for differences in returns between the skip-day portfolios and their non-skip-day counterparts. However, we have not actually performed any statistical tests of this difference for out data.

Since we do not have the bid-quotations necessary to perform the bid-bid procedure mentioned in chapter 3, this procedure could not be used to see whether it would give more information on what effect the bid-ask bounce has on the results. Our test is performed using relatively liquid large-capitalization stocks that are less likely to be significantly affected by the bid-ask bounce than low liquidity stocks. This fact in combination with the information from the filters and the skip-day method lead us to believe that the small reversal effect found is at least not the result of the bid-ask bounce alone. However, the bid-ask bounce cannot be ruled out as a possible explanation to some part of the reversal effect.

6.4 Price and Volume Strategies

This section contains an analysis of the results from the first-order price and volume strategies:

1. Loser-price negative-growth-in-volume
2. Loser-price positive-growth-in-volume
3. Winner-price negative-growth-in-volume
4. Winner-price positive-growth-in-volume

By incorporating a lagged volume measure into the portfolio formation rule, the relation between lagged volume and future price changes can be analyzed. Cooper finds evidence that reversals for both winners and losers are larger when the trading volume is small. He takes this as evidence in favor of Wang's hypothesis that a possible explanation to the reversals is that there are two different types of investors trading in the market: those who possess private information and those who do not. According to Wang, positive-growth-in-volume stocks tend to exhibit weaker reversals and maybe even positive autocorrelation, and negative-growth-in-volume stocks should experience larger reversals. This effect could of course also be caused by the bid-ask bounce effect, which can have a larger influence when the trading volume is low.

Our winner portfolio results are very weak, but they do not seem to contradict Wang's hypothesis since there appears to be a pattern of larger returns when the volume is high compared to when it is low. For the largest growth-in-volume filter-level, four of the winner portfolios generate positive returns that are statistically significant. For the winner-price negative-growth-in-volume strategies, 16 of the portfolios have a slightly negative return, whereas only six of the winner-price positive-growth-in-volume strategies have a negative return.

Although many of the returns are not statistically significant, they give an indication of what effect the volume has on the reversal effect. Large increases in price accompanied with low lagged volume tend to be reversed more than large increases accompanied with high lagged volume. However, for the loser portfolios, the result of applying a volume filter is that the stocks are spread across too many portfolios and the portfolio returns appear to be random.

Can Volume Help to Explain the Asymmetry Discussed Earlier?

If cross-autocorrelation among securities caused a substantial part of the positive winner-price portfolio returns, larger reversals would be expected at higher levels of trading volume. The reason for this is that cross-autocorrelation should decrease as the liquidity in the market increases. Since the cross-autocorrelation works in a direction opposite to that of the overreaction effect for winners, lower levels of cross-autocorrelation should lead to larger reversals for winners.

The fact that there is no evidence that larger volume filters generate larger winner portfolio reversals could be an indication that cross-autocorrelation across securities is not the main source of the positive returns found for the winner portfolios.

6.5 Analysis of Portfolio Excess Return

Unlike Cooper, we find the excess returns generated by the different portfolios more interesting than the absolute returns, since an overreaction effect is easier to identify using excess returns. The benchmark comparison is used to mitigate one component of the survivorship bias, namely the displacement of the mean return. In addition, it is more economically meaningful to compare the return of an investment strategy with the return on an alternative investment instead of a zero-return investment.

Price Strategies

For the first-order loser-price benchmark portfolios, only the most extreme filter portfolio has a significant (positive) return. This can be compared to the portfolios that were tested against a zero return instead of the benchmark, that generated positive returns significantly different from zero in four of the portfolios. There are no significant loser-loser-price portfolio excess returns.

For the first-order winner-price benchmark portfolios, the only significant (negative) return is for the most extreme portfolio. The same pattern is found for the second-order winner, winner-price portfolios.

This shows that the most extreme first-order-price portfolios exhibit a statistically significant reversal effect. This result is consistent with the results of other studies where an extreme "ten-percent-up-or-down" criterion has been used to test for an overreaction effect.

Price-Volume Strategies

There is still no evident reversal effect in the price-and-volume-filter-portfolio excess returns. The previous conclusions regarding volume do not change when comparing to the benchmark. However, since the returns are lower for all the portfolios, most of the portfolio returns that were significant before the benchmark was deducted are now insignificant.

Chapter 7

Summary and Conclusions

This thesis tests for an overreaction effect on the Stockholm stock exchange A-list using data for the period January 4 1982 through August 30 1999. The test is basically a replication of some parts of a test successfully employed by Cooper (Cooper, 1999) on the American stock markets NYSE and AMEX. The thesis also contains an overview of the theory and previous empirical findings on the overreaction effect.

In the test for overreaction effects, significant reversal effects are found for several of the first-order loser-price strategies. A consistent pattern of larger (smaller) returns is found for the losers (winners) at the more extreme filter levels. The second-order price portfolios are less likely to experience a significant reversal than their first-order counterparts.

When volume is incorporated in the portfolio formation rule, high-growth-in-volume stocks tend to exhibit weaker reversals and even positive autocorrelation, and low-growth-in-volume stocks tend to experience larger reversals. We believe that one reason for this could be that the negative (positive) excess return earned by the winners (losers) is spread out over the 12 different volume-filter levels. In this aspect, the incorporation of volume makes the picture of the overreaction effect less clear.

When comparing the portfolio returns to a benchmark the apparent asymmetry in the overreaction effect disappear. For the price-only strategies, winner and loser portfolios exhibit a significant reversal effect at the most extreme filter-levels. For the less extreme filter-levels -4 through 3 there is a non-significant positive autocorrelation in all but one portfolio.

Since the sample period, data sources and our methodology is different from earlier overreaction effect studies, our results are not expected to be the same. Nevertheless, it is interesting to see that the excess returns earned at the most extreme price filter levels are similar to the results in many of the previous tests.

We believe that the returns earned by the portfolios after the benchmark portfolio returns have been deducted give us a better picture of the overreaction effect. After the benchmark has been deducted, it will be easier to see what part of the portfolio returns is specific to the stocks in the portfolio, and not just the result of the general trend in the stock market.

The reversal effect for the price portfolios at the most extreme filter-levels could have been exploited by an ideal investor using a contrarian strategy. An investor who had gone long in losers and short in winners would have had a positive excess return for the studied period, given that transaction costs and brokerage fees were zero, and that he knew in advance which stocks would survive until the end of the period.

One obvious explanation to the excess return generated by such a strategy is that the stocks experiencing short-term reversals could be riskier than other stocks. In the test, no attempt was made to measure the risk and therefore no conclusions can be draw from the result about market efficiency. The fact that brokerage fees and other transaction costs have not been taken into account when calculating the portfolio returns allows for the possibility that the effect is too small to be traded away.

Another explanation an advocate of the EMH might suggest is that the premium return has a micro-structural explanation or that it is caused by other systematic errors in the model specification used to find the premium profits. The analysis indicates that the results are not likely to have been caused entirely by the bid-ask bounce effect or cross-autocorrelation across securities.

Yet another explanation is that there may be methodological mistakes in the test. For example, there is a survivorship bias in the data, which may actually have caused an apparent overreaction effect.

The results indicate a small but statistically significant reversal of portfolios of the most extreme winners and losers. The results are not as unambiguous as those of Cooper's survey are. When using a first-order-price filter, the most extreme portfolios are significant and consistent with the overreaction effect. However, for the second-order-price and first-order-price-and-volume filter the results are difficult to interpret, and could have been caused by random perturbations. It would be difficult to trade successfully using these findings alone, if trading costs, such as the bid-ask spread and brokerage fees are taken into account.

We believe that the significant results that have been found are not caused by the bid-ask-bounce effect to any large extent. However, they could have been caused by a survivorship bias in the data. In addition, the results can be consistent with the efficient market hypothesis if the risk premium is allowed to be time varying.

Appendix A

Results

A.1 Density of Available Data

The density of the available valid data is found in figure A.1.

A.2 Price Filter Return

The loser-price return is found in table A.1. The winner-price return is found in table A.2. The first order price return is plotted in figure A.2. The second order price return is plotted in figure A.3.

A.3 Price Filter Excess Return

The loser-price excess return is found in table A.3. The winner-price excess return is found in table A.4. The first-order price filter excess return is plotted in figure A.4. The second-order price filter excess return is plotted in figure A.5.

A.4 Price and Volume Filter Return

A.4.1 Absolute Returns

The returns of the loser-price negative-growth-in-volume price-volume filter strategies are listed in table A.5. The returns of the loser-price positive-growth-in-volume price-volume filter strategies are listed in table A.6. The returns of the winner-price negative-growth-in-volume price-volume filter strategies are listed in table A.7. The returns of the winner-price positive-growth-

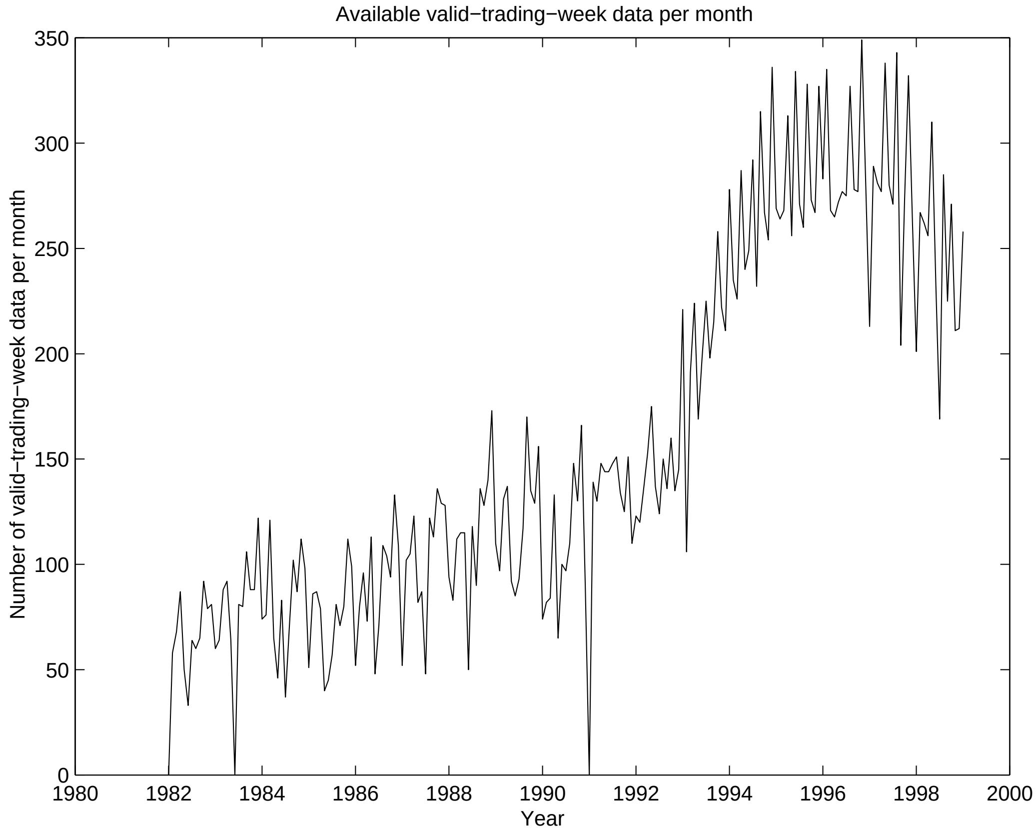

Figure A.1: The density of available valid data

in-volume price-volume filter strategies are listed in table A.8. The result of the first order price and volume filter is plotted in figure A.6.

The returns of the winner-price positive-growth-in-volume price-volume filter strategies are listed in table A.8. The result of the first order price and volume filter is plotted in figure A.6.

A.4.2 Excess Returns

The excess returns of the loser-price negative-growth-in-volume price-volume filter strategies are listed in table A.9. The excess returns of the loser-price positive-growth-in-volume price-volume filter strategies are listed in table A.10. The excess returns of the winner-price negative-growth-in-volume price-volume filter strategies are listed in table A.11. The excess returns of the winner-price positive-growth-in-volume price-volume filter strategies are listed in table A.12. The excess return of the first order price and volume

Strategy	Filter counter	-6	-5	-4	-3	-2	-1
Loser-price	Mean/%	1.44	0.83	0.05	0.44	0.32	0.28
	Std. dev./%	7.87	5.70	5.67	4.63	4.49	3.56
	N	247	233	399	558	697	739
	t-statistic	2.88	2.23	0.16	2.23	1.91	2.12
Skip-day loser-price	Mean/%	0.93	0.38	0.76	0.50	0.39	0.44
	Std. dev./%	8.83	7.40	5.66	4.80	4.00	3.35
	N	203	202	361	540	707	744
	t-statistic	1.50	0.73	2.55	2.40	2.61	3.56
Loser, loser-price	Mean/%	1.85	-0.81	-0.66	0.13	0.29	-0.05
	Std. dev./%	11.82	7.83	6.70	5.46	5.04	3.60
	N	36	18	39	100	281	401
	t-statistic	0.94	-0.44	-0.61	0.23	0.96	-0.26
Skip-day loser, loser-price	Mean/%	1.40	-2.15	-0.29	0.83	0.13	0.27
	Std. dev./%	9.76	5.87	7.08	10.94	4.21	3.61
	N	22	10	36	97	292	443
	t-statistic	0.67	-1.16	-0.24	0.75	0.54	1.60

Table A.1: The result of the loser price filter strategies

filter is plotted in figure A.7.

Strategy	Filter counter	0	1	2	3	4	5
Winner-price	Mean/%	0.45	0.54	0.45	0.44	-0.01	-0.41
	Std. dev./%	3.69	3.84	4.18	5.21	4.87	5.84
	N	762	695	618	494	391	400
	t-statistic	3.33	3.68	2.66	1.88	-0.05	-1.42
Skip-day winner-price	Mean/%	0.45	0.35	0.25	0.26	-0.33	-0.21
	Std. dev./%	3.41	3.77	4.19	4.57	4.82	6.03
	N	762	689	601	469	304	342
	t-statistic	3.66	2.43	1.48	1.21	-1.18	-0.63
Winner, winner-price	Mean/%	0.55	0.77	0.96	0.38	0.56	-1.63
	Std. dev./%	3.65	4.47	5.28	7.61	3.47	7.66
	N	547	307	145	49	18	61
	t-statistic	3.50	3.02	2.19	0.35	0.69	-1.66
Skip-day winner, winner-price	Mean/%	0.41	0.27	1.14	-0.26	-0.31	-2.71
	Std. dev./%	3.44	3.58	5.05	3.61	7.22	10.03
	N	579	297	116	41	6	41
	t-statistic	2.85	1.32	2.43	-0.46	-0.11	-1.73

Table A.2: The result of the winner price filter strategies

Strategy	Filter counter	-6	-5	-4	-3	-2	-1
Loser-price	Mean/%	1.06	0.45	-0.34	0.06	-0.06	-0.11
	Std. dev./%	0.51	0.39	0.30	0.22	0.20	0.17
	df	1023	1009	1175	1334	1473	1515
	t-statistic	2.07	1.16	-1.11	0.25	-0.29	-0.62
Loser, loser-price	Mean/%	1.48	-1.18	-1.03	-0.25	-0.09	-0.42
	Std. dev./%	1.98	1.85	1.08	0.57	0.34	0.23
	df	734	716	737	798	979	1099
	t-statistic	0.75	-0.64	-0.96	-0.44	-0.26	-1.81

Table A.3: The excess return of the loser-price strategies

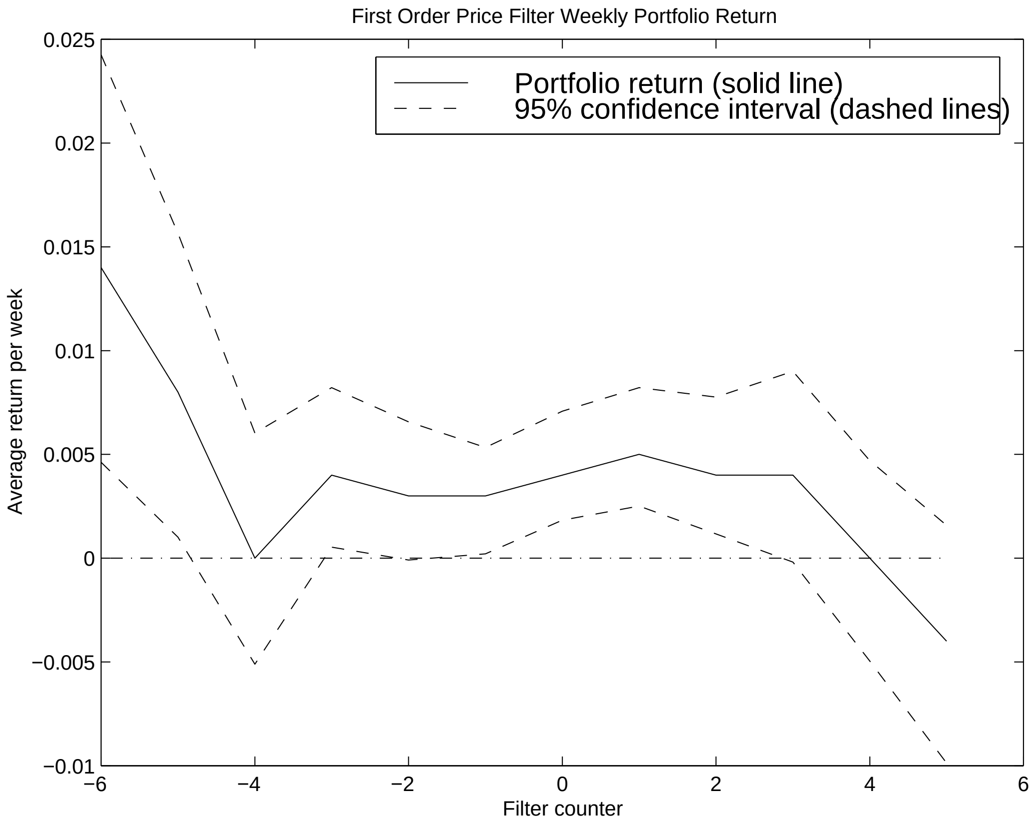

Figure A.2: The result of the first order price filter

Strategy	Filter counter	0	1	2	3	4	5
Winner-price	Mean/%	0.06	0.15	0.06	0.06	-0.40	-0.80
	Std. dev./%	0.17	0.18	0.20	0.26	0.27	0.31
	df	1538	1471	1394	1270	1167	1176
	t-statistic	0.36	0.84	0.32	0.22	-1.47	-2.55
Winner, winner-price	Mean/%	0.17	0.39	0.58	0.00	0.18	-2.01
	Std. dev./%	0.22	0.30	0.46	1.10	0.83	0.99
	df	1245	1005	843	747	716	759
	t-statistic	0.78	1.33	1.26	0.00	0.22	-2.02

Table A.4: The excess return of the winner-price strategies

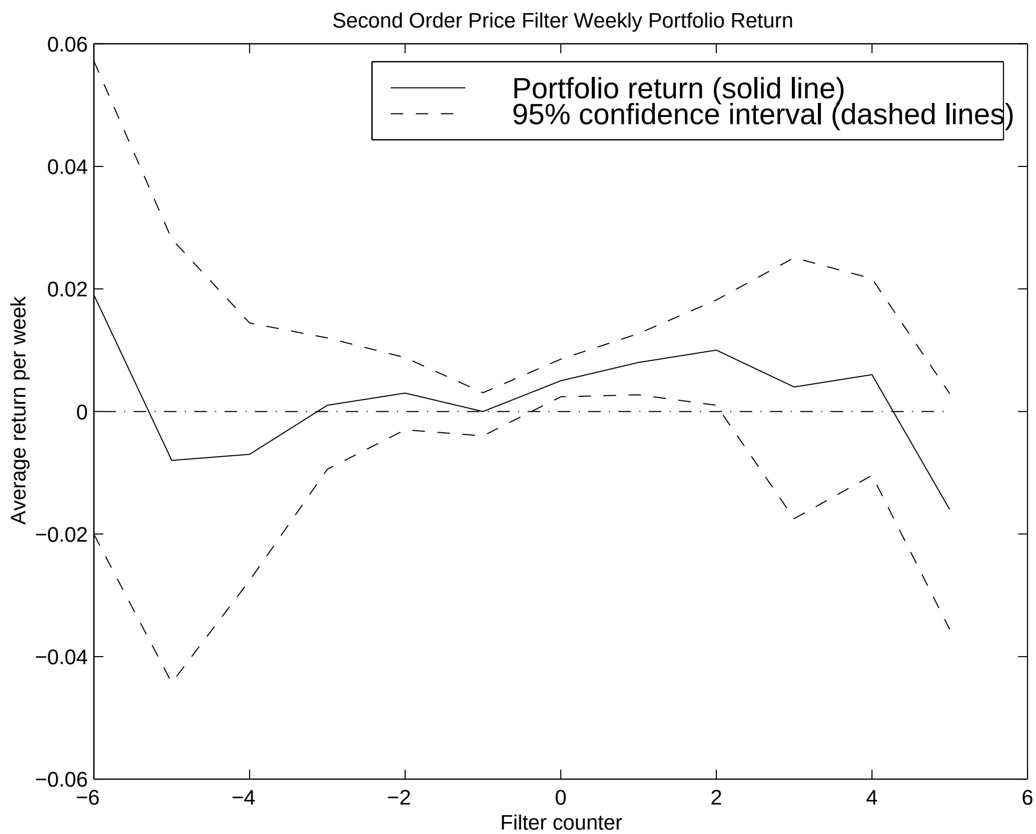

Figure A.3: The result of the second order price filter

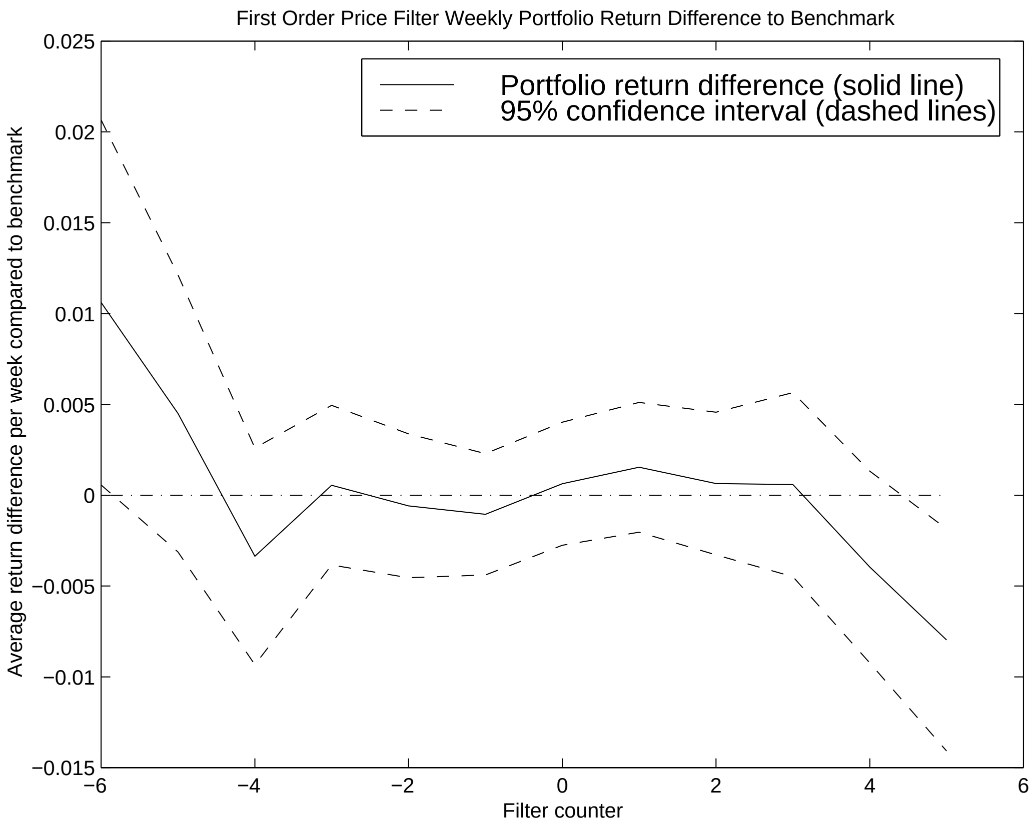

Figure A.4: The excess return of the first order price filter

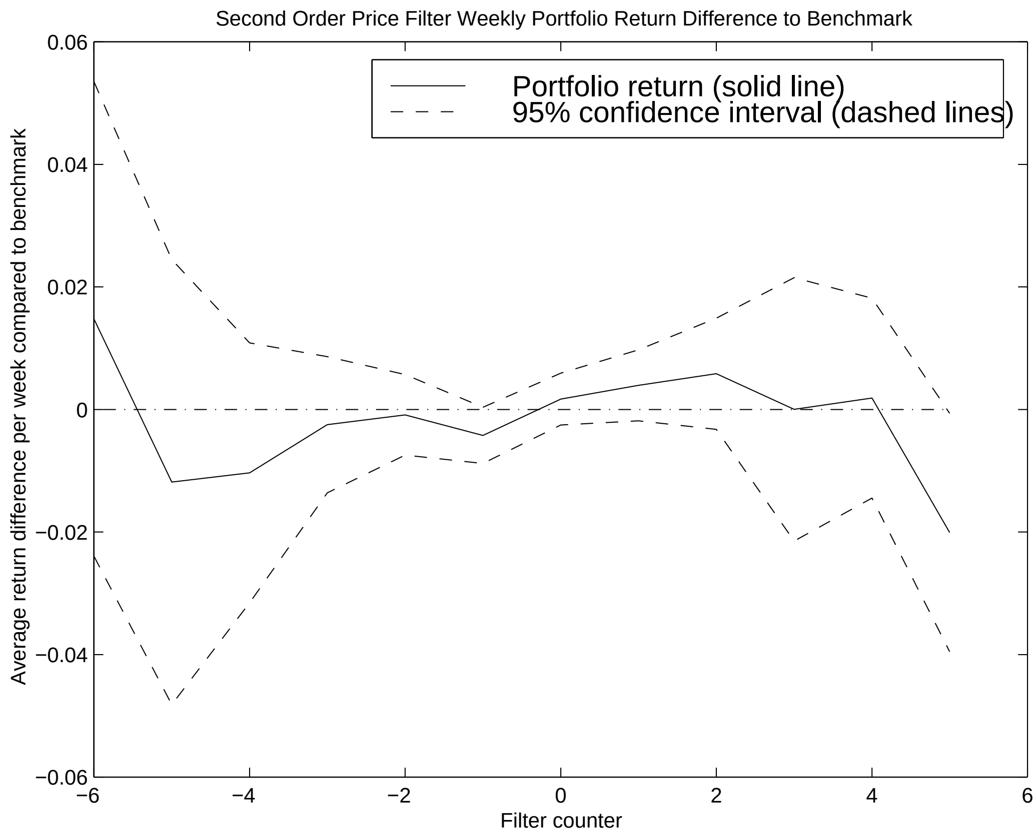

Figure A.5: The excess return of the second order price filter

Volume filter counter	Price Filter counter	-6	-5	-4	-3	-2	-1
-6	Mean/%	1.38	1.48	0.85	0.56	-0.05	-0.54
	Std. dev./%	11.48	4.98	5.27	5.52	4.61	4.24
	N	16	12	26	79	150	176
	t-statistic	0.48	1.03	0.82	0.91	-0.14	-1.68
-5	Mean/%	0.47	1.55	1.82	0.87	0.58	0.13
	Std. dev./%	8.95	5.04	6.79	5.45	4.37	4.02
	N	29	24	66	119	233	259
	t-statistic	0.28	1.51	2.17	1.73	2.02	0.51
-4	Mean/%	1.94	0.34	0.72	0.46	-0.09	0.25
	Std. dev./%	9.66	6.64	6.51	5.78	4.28	4.09
	N	37	33	75	147	294	330
	t-statistic	1.22	0.29	0.96	0.95	-0.37	1.11
-3	Mean/%	1.20	1.74	0.05	0.56	0.51	0.58
	Std. dev./%	9.29	7.14	5.24	5.55	4.72	3.92
	N	44	33	76	157	279	331
	t-statistic	0.86	1.40	0.08	1.27	1.82	2.69
-2	Mean/%	0.62	0.30	0.99	0.15	0.39	0.25
	Std. dev./%	7.87	5.49	7.28	5.27	4.92	3.82
	N	35	37	90	160	255	312
	t-statistic	0.46	0.34	1.30	0.35	1.26	1.16
-1	Mean/%	7.20	0.93	0.49	0.67	0.08	0.18
	Std. dev./%	10.42	5.31	6.58	5.31	4.67	4.60
	N	27	28	65	127	233	285
	t-statistic	3.59	0.93	0.61	1.41	0.25	0.67

Table A.5: The return of the loser-price negative-growth-in-volume price-volume filter strategies

Volume filter counter	Price Filter counter	-6	-5	-4	-3	-2	-1
0	Mean/%	0.32	1.07	0.59	0.33	0.00	0.42
	Std. dev./%	8.50	6.29	5.77	4.88	4.06	4.27
	N	73	68	150	244	370	420
	t-statistic	0.32	1.41	1.25	1.06	0.01	2.02
1	Mean/%	1.76	0.08	1.20	0.34	0.47	0.27
	Std. dev./%	10.69	7.27	5.43	4.14	4.66	4.20
	N	68	43	73	127	212	277
	t-statistic	1.36	0.07	1.89	0.93	1.47	1.06
2	Mean/%	2.13	0.84	-0.86	-0.56	-0.06	-0.04
	Std. dev./%	7.30	6.71	7.55	4.04	5.34	5.74
	N	36	28	46	73	121	129
	t-statistic	1.75	0.66	-0.78	-1.18	-0.13	-0.07
3	Mean/%	0.00	1.93	1.27	-0.12	0.86	-0.25
	Std. dev./%	9.00	5.21	5.96	6.88	5.09	3.78
	N	25	13	33	40	58	97
	t-statistic	0.00	1.34	1.22	-0.11	1.29	-0.66
4	Mean/%	1.95	1.89	-0.75	0.01	2.34	0.73
	Std. dev./%	10.24	5.34	5.51	6.00	10.92	3.15
	N	13	16	21	29	44	41
	t-statistic	0.69	1.42	-0.62	0.01	1.42	1.49
5	Mean/%	0.86	0.24	-0.60	0.18	-0.50	0.15
	Std. dev./%	9.97	5.84	5.47	3.82	6.25	3.90
	N	41	34	39	61	107	126
	t-statistic	0.55	0.24	-0.69	0.37	-0.83	0.44

Table A.6: The return of the loser-price positive-growth-in-volume price-volume filter strategies

Volume filter counter	Price Filter counter	0	1	2	3	4	5
-6	Mean/%	0.25	-0.22	0.92	-0.10	0.54	0.92
	Std. dev./%	4.10	4.28	5.07	5.34	3.22	3.36
	N	209	100	41	25	12	5
	t-statistic	0.88	-0.52	1.17	-0.09	0.59	0.61
-5	Mean/%	0.04	0.31	0.50	0.19	-2.49	-1.35
	Std. dev./%	4.06	4.55	5.50	4.51	6.10	6.30
	N	294	146	74	30	12	16
	t-statistic	0.16	0.82	0.78	0.24	-1.41	-0.86
-4	Mean/%	-0.14	0.09	0.11	-1.49	-0.06	-0.91
	Std. dev./%	3.79	5.15	6.52	4.02	5.28	6.37
	N	370	200	116	44	18	30
	t-statistic	-0.71	0.25	0.18	-2.46	-0.05	-0.78
-3	Mean/%	-0.03	0.86	0.12	-0.11	-0.06	-0.74
	Std. dev./%	4.43	4.96	4.89	5.94	8.78	5.21
	N	405	240	139	72	37	44
	t-statistic	-0.13	2.68	0.29	-0.15	-0.04	-0.94
-2	Mean/%	0.59	0.59	0.31	0.26	-1.00	-3.73
	Std. dev./%	4.26	5.05	4.65	5.97	5.11	8.11
	N	393	267	149	94	35	41
	t-statistic	2.76	1.90	0.80	0.42	-1.16	-2.94
-1	Mean/%	0.34	0.40	0.23	-0.02	-0.70	-1.05
	Std. dev./%	4.58	4.51	4.38	5.42	4.98	6.78
	N	372	231	147	85	47	38
	t-statistic	1.42	1.34	0.63	-0.03	-0.96	-0.95

Table A.7: The return of the winner-price negative-growth-in-volume price-volume filter strategies

Volume filter counter	Price Filter counter	0	1	2	3	4	5
0	Mean/%	0.20	0.48	0.11	0.77	0.41	-0.26
	Std. dev./%	3.85	4.68	4.84	7.82	5.65	5.61
	N	522	397	282	214	111	134
	t-statistic	1.16	2.06	0.37	1.44	0.77	-0.55
1	Mean/%	0.81	0.52	1.06	0.19	0.15	0.84
	Std. dev./%	5.46	4.20	5.31	5.35	4.71	7.75
	N	354	263	209	135	89	102
	t-statistic	2.79	2.00	2.88	0.42	0.31	1.09
2	Mean/%	0.51	0.28	0.32	0.98	-0.32	0.18
	Std. dev./%	4.08	4.25	4.89	5.63	4.57	7.42
	N	243	176	123	93	61	89
	t-statistic	1.95	0.87	0.73	1.68	-0.54	0.23
3	Mean/%	1.05	0.21	-0.15	1.59	2.56	-0.12
	Std. dev./%	6.85	4.84	4.70	4.81	5.89	8.54
	N	131	109	91	60	36	58
	t-statistic	1.75	0.44	-0.30	2.56	2.60	-0.10
4	Mean/%	0.57	0.74	1.23	2.27	0.28	-0.83
	Std. dev./%	3.53	4.54	6.33	5.56	3.55	6.12
	N	87	70	64	34	32	47
	t-statistic	1.50	1.36	1.56	2.37	0.45	-0.94
5	Mean/%	0.63	1.29	1.00	1.43	0.25	0.62
	Std. dev./%	4.07	4.25	5.13	5.72	4.93	6.21
	N	227	154	141	98	71	105
	t-statistic	2.33	3.76	2.31	2.48	0.42	1.02

Table A.8: The return of the winner-price positive-growth-in-volume price-volume filter strategies

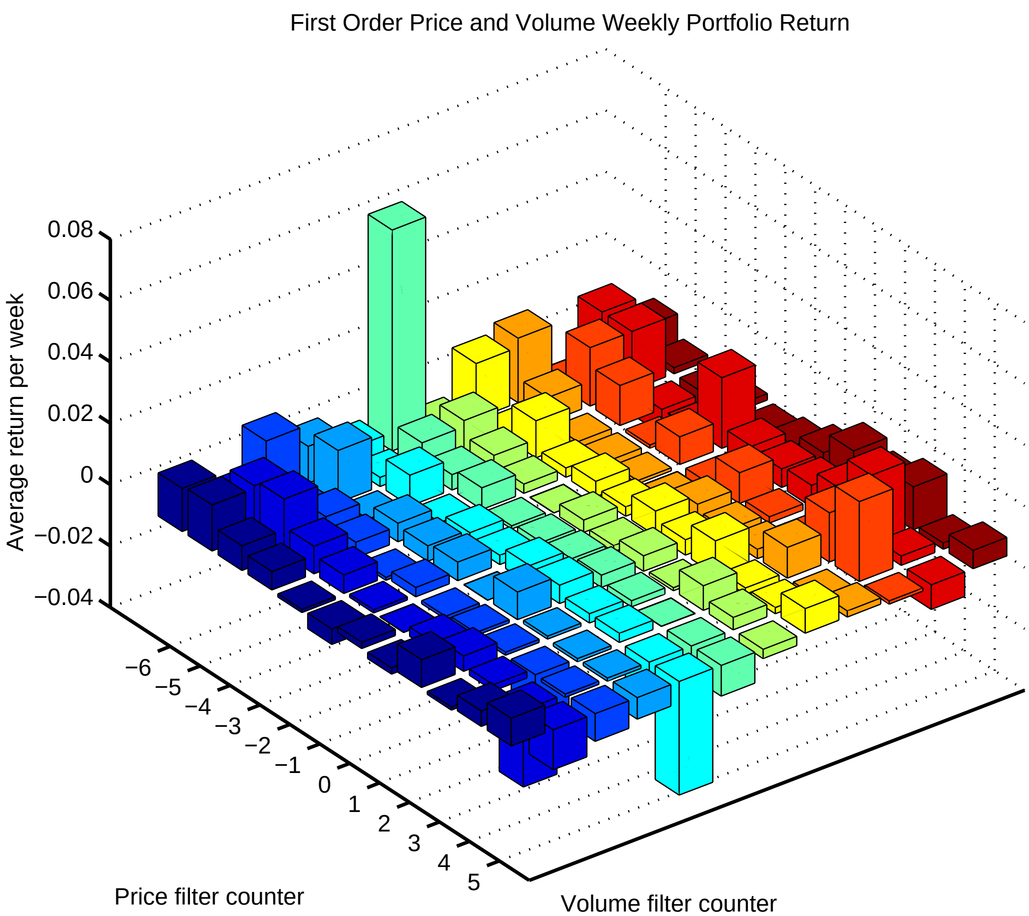

Figure A.6: The result of the first order price and volume filter

Volume filter counter	Price Filter counter	-6	-5	-4	-3	-2	-1
-6	Mean/%	1.00	1.10	0.47	0.18	-0.43	-0.92
	Std. dev./%	2.87	1.44	1.04	0.63	0.39	0.34
	df	746	742	756	809	880	906
	t-statistic	0.35	0.76	0.45	0.29	-1.10	-2.69
-5	Mean/%	0.09	1.17	1.44	0.49	0.20	-0.25
	Std. dev./%	1.67	1.04	0.84	0.51	0.31	0.28
	df	759	754	796	849	963	989
	t-statistic	0.05	1.13	1.70	0.95	0.64	-0.91
-4	Mean/%	1.56	-0.04	0.34	0.08	-0.47	-0.13
	Std. dev./%	1.59	1.16	0.76	0.49	0.28	0.25
	df	767	763	805	877	1024	1060
	t-statistic	0.98	-0.04	0.45	0.15	-1.71	-0.51
-3	Mean/%	0.82	1.36	-0.33	0.18	0.13	0.20
	Std. dev./%	1.40	1.25	0.61	0.46	0.31	0.25
	df	774	763	806	887	1009	1061
	t-statistic	0.59	1.09	-0.54	0.40	0.44	0.81
-2	Mean/%	0.24	-0.08	0.61	-0.23	0.01	-0.13
	Std. dev./%	1.34	0.91	0.78	0.43	0.33	0.25
	df	765	767	820	890	985	1042
	t-statistic	0.18	-0.08	0.79	-0.54	0.02	-0.53
-1	Mean/%	6.82	0.55	0.11	0.29	-0.30	-0.20
	Std. dev./%	2.01	1.01	0.82	0.49	0.33	0.30
	df	757	758	795	857	963	1015
	t-statistic	3.40	0.54	0.14	0.59	-0.93	-0.67

Table A.9: The excess return of the loser-price negative-growth-in-volume price-volume filter strategies

Volume filter counter	Price Filter counter	-6	-5	-4	-3	-2	-1
0	Mean/%	-0.06	0.69	0.21	-0.05	-0.38	0.04
	Std. dev./%	1.00	0.77	0.49	0.33	0.24	0.24
	df	803	798	880	974	1100	1150
	t-statistic	-0.06	0.90	0.43	-0.14	-1.57	0.17
1	Mean/%	1.38	-0.30	0.82	-0.04	0.09	-0.11
	Std. dev./%	1.30	1.11	0.65	0.39	0.34	0.28
	df	798	773	803	857	942	1007
	t-statistic	1.06	-0.27	1.27	-0.10	0.26	-0.40
2	Mean/%	1.75	0.46	-1.24	-0.94	-0.44	-0.42
	Std. dev./%	1.22	1.27	1.12	0.49	0.50	0.52
	df	766	758	776	803	851	859
	t-statistic	1.43	0.36	-1.11	-1.93	-0.89	-0.80
3	Mean/%	-0.38	1.55	0.89	-0.50	0.48	-0.63
	Std. dev./%	1.80	1.45	1.04	1.09	0.68	0.40
	df	755	743	763	770	788	827
	t-statistic	-0.21	1.07	0.85	-0.46	0.71	-1.58
4	Mean/%	1.57	1.51	-1.13	-0.37	1.96	0.35
	Std. dev./%	2.84	1.34	1.21	1.12	1.65	0.51
	df	743	746	751	759	774	771
	t-statistic	0.55	1.13	-0.94	-0.33	1.19	0.69
5	Mean/%	0.48	-0.14	-0.98	-0.20	-0.88	-0.23
	Std. dev./%	1.56	1.01	0.88	0.50	0.62	0.37
	df	771	764	769	791	837	856
	t-statistic	0.31	-0.14	-1.11	-0.39	-1.44	-0.62

Table A.10: The excess return of the loser-price positive-growth-in-volume price-volume filter strategies

Volume filter counter	Price Filter counter	0	1	2	3	4	5
-6	Mean/%	-0.13	-0.60	0.54	-0.48	0.16	0.54
	Std. dev./%	0.31	0.44	0.80	1.07	0.94	1.51
	df	939	830	771	755	742	735
	t-statistic	-0.43	-1.36	0.68	-0.44	0.18	0.36
-5	Mean/%	-0.34	-0.07	0.12	-0.19	-2.87	-1.73
	Std. dev./%	0.26	0.39	0.65	0.83	1.76	1.58
	df	1024	876	804	760	742	746
	t-statistic	-1.29	-0.18	0.18	-0.22	-1.63	-1.09
-4	Mean/%	-0.52	-0.29	-0.27	-1.87	-0.44	-1.29
	Std. dev./%	0.23	0.38	0.62	0.62	1.25	1.17
	df	1100	930	846	774	748	760
	t-statistic	-2.27	-0.76	-0.44	-3.03	-0.35	-1.11
-3	Mean/%	-0.41	0.48	-0.26	-0.49	-0.44	-1.12
	Std. dev./%	0.25	0.34	0.43	0.71	1.45	0.79
	df	1135	970	869	802	767	774
	t-statistic	-1.64	1.41	-0.60	-0.68	-0.31	-1.41
-2	Mean/%	0.21	0.21	-0.07	-0.12	-1.38	-4.11
	Std. dev./%	0.24	0.33	0.40	0.63	0.87	1.27
	df	1123	997	879	824	765	771
	t-statistic	0.87	0.63	-0.19	-0.19	-1.59	-3.23
-1	Mean/%	-0.04	0.02	-0.15	-0.40	-1.08	-1.43
	Std. dev./%	0.26	0.32	0.38	0.60	0.74	1.11
	df	1102	961	877	815	777	768
	t-statistic	-0.17	0.05	-0.40	-0.66	-1.47	-1.29

Table A.11: The excess return of the winner-price negative-growth-in-volume price-volume filter strategies

Volume filter counter	Price Filter counter	0	1	2	3	4	5
0	Mean/%	-0.18	0.10	-0.27	0.39	0.03	-0.64
	Std. dev./%	0.20	0.26	0.31	0.55	0.55	0.50
	df	1252	1127	1012	944	841	864
	t-statistic	-0.90	0.40	-0.88	0.71	0.06	-1.29
1	Mean/%	0.43	0.14	0.68	-0.19	-0.23	0.46
	Std. dev./%	0.31	0.28	0.39	0.47	0.51	0.78
	df	1084	993	939	865	819	832
	t-statistic	1.37	0.48	1.76	-0.39	-0.44	0.59
2	Mean/%	0.13	-0.10	-0.06	0.60	-0.70	-0.20
	Std. dev./%	0.29	0.34	0.46	0.59	0.60	0.79
	df	973	906	853	823	791	819
	t-statistic	0.46	-0.30	-0.12	1.01	-1.17	-0.25
3	Mean/%	0.67	-0.17	-0.53	1.21	2.18	-0.50
	Std. dev./%	0.61	0.48	0.51	0.63	0.99	1.13
	df	861	839	821	790	766	788
	t-statistic	1.10	-0.37	-1.04	1.91	2.20	-0.44
4	Mean/%	0.19	0.36	0.85	1.89	-0.10	-1.21
	Std. dev./%	0.40	0.56	0.80	0.96	0.64	0.90
	df	817	800	794	764	762	777
	t-statistic	0.47	0.65	1.07	1.96	-0.15	-1.35
5	Mean/%	0.25	0.91	0.62	1.05	-0.13	0.24
	Std. dev./%	0.29	0.36	0.45	0.59	0.60	0.62
	df	957	884	871	828	801	835
	t-statistic	0.85	2.51	1.38	1.79	-0.22	0.39

Table A.12: The excess return of the winner-price positive-growth-in-volume price-volume filter strategies

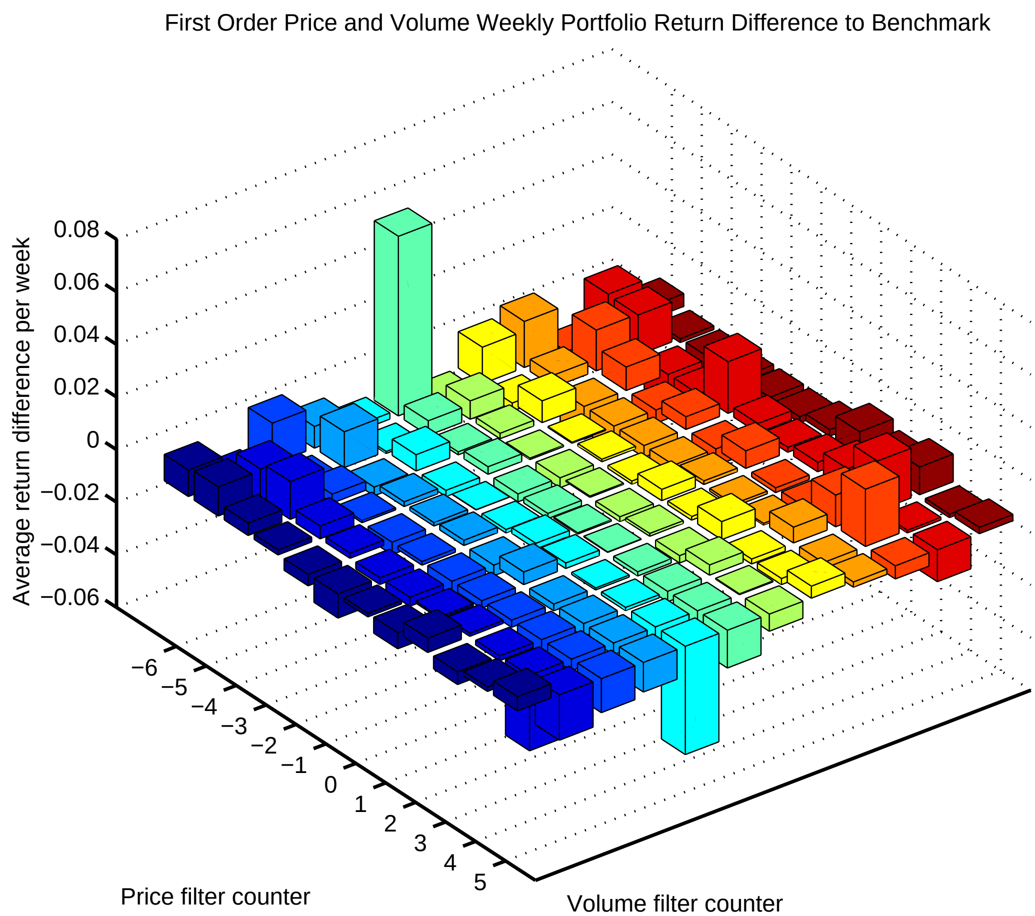

Figure A.7: The excess return of the first order price and volume filter

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