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RETURNS ON VOLUME-BASED PORTFOLIOS IN THE HELSINKI STOCK EXCHANGE

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Abstract

More than fifty variables have been shown to have predictive power over expected returns. In a sample of NYSE/AMEX stocks, Lee and Swaminathan (2000) show that share turnover is negatively related to future returns. Also Wang and Chin (2004) find that portfolios of low trading volume outperform portfolios of high trading volume with the difference in returns more pronounced for past winners than for past losers in a sample of Shanghai and Shenzhen stocks. Motivated by these findings, I extend the study on the volume – return dynamics using data from the Helsinki Stock Exchange. In this paper, I study the informational content present in trading volume in the prediction of expected returns. More importantly, I examine the profitability of various volume based portfolios.

Following the methodology of Jegadeesh and Titman (1993) and inspired by Wang and Chin (2004), I form portfolios based on past returns and trading volume over different formation and holding periods and examine the profitability of various volume based portfolio strategies over the period from 1999 to 2010.

I find that conditional on past returns, high-volume stocks outperform low volume stocks for most formation and holding periods. The volume discount, that is the average monthly returns difference between low volume portfolios and high-volume portfolios, is largest in magnitude for the 6 x 12 strategy for winners portfolios at -2.17% (*t*-statistics = -4.70). The results are robust to risk adjustment relative to the Fama and French (1993) three factor model. The results are not entirely consistent with the existing literature on the volume-return dynamics. While the results suggest that investing in high-volume stocks and shorting portfolios of low-volume stocks is a profitable strategy, implementing such trading strategy should be done with caution because of the special nature of the Helsinki Stock Exchange.

Keywords
Asset returns, trading activity, volume discounts, Helsinki Stock Exchange

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1 INTRODUCTION

1.1 Introduction to subject matter

One single area in finance that has attracted so much attention is the field of asset pricing. The academic literature in Finance has for several decades concluded that stock markets are informationally efficient. The earliest empirical work of Fama (1970) suggests that any trading strategy that utilizes past trading data, public and private information is close to being useless and will at best compensate for the cost of such information gathering and transaction costs. However over the last three decades, a growing number of financial literatures now document empirical evidences that prove otherwise. For example, De Bondt and Thaler (1985) document long term price reversals in which past losers outperform past winners over the subsequent three to five years after portfolio formation. They attribute their evidence to overreaction hypothesis which is evidence against weak form market efficiency. Jegadeesh (1990) also show that contrarian investment strategies that buy stocks which have performed worse over the past months and sell stocks which have performed better over same period generates abnormal returns that are statistically and economically significant. Lehmann (1990, 1993) also document that contrarian strategies based on past weekly returns exhibit return reversals.

Subsequently, returns which had hitherto been thought of to be unpredictable are indeed predictable. Factors such as momentum, size, value, dividend-price ratio, growth, profitability, past sales growth have been shown to have predictable capability over future returns. Though there exists countless number of published papers regarding the extent of their returns predictive power, these factors have been shown to explain asset returns with varying levels of return predicting powers.

Most of these returns predicting phenomena deviate largely from the Capital Asset Pricing Model (CAPM) which has been thought of to fully explain asset returns. Because of the deviations of these phenomena from the CAPM, Fama and French (1996) referred to them as anomalies. In much of the papers devoted to understanding patterns of stock returns predictability, there has been divergent discourse on the reasons for returns predictability. While most academics have attributed much of the returns predictability to behavioural biases on the part of investment practitioners, others have simply argued that markets are efficient and the results of the predictable returns pattern could be attributed to model misspecification or wrong choice of methodology. See Fama (1998).

In this paper, I study an element of stock returns predictability that relates to trading volume. I use share turnover as a proxy for trading volume although this measure do not fully take into account the relative importance of differences in shareholder base[1]. Wang and Chin (2004) use tradable turnover in their study which takes into account the effect of shareholder base and differences in number of shares outstanding. In addition, I examine the informational role that is present in past trading volume and past returns as it relates to future abnormal returns. While most practitioners utilize some elements of liquidity based decisions in their trading strategies, the extent of the informational role of such liquidity measures is not fully known. Earlier empirical works have in the most part focused on understanding the relationship between volume and contemporaneous returns. For a quick review of previous research on the volume-return relationship, see Karpoff (1987).

Liquidity which is closely related to trading volume has long been associated with negative relationship with stock returns. Amihud and Mendelson (1986) use the bid-ask spread to study the behaviour of asset returns and find that the expected return of assets is related to the magnitude of the difference between the bid-ask spread. An investor holding an asset with high bid-ask spread faces a restriction when selling the asset and thus, the return on the assets increases with the holding period. In explaining this phenomenon of predictable asset return based on liquidity measures such as the bid-ask spread, Amihud and Mendelson (1986: 224) argue that their result is consistent with a "rational response by an efficient market to the existence of the spread" and they do not see it as an anomaly. Brennan *et al.* (1998) also find significant negative relationship between average stock returns and trading volume which they attribute to the liquidity premium hypothesis[2].

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[1] To illustrate the concept of tradable turnover, assume two firms, A and B, with same shares outstanding of 1000 units and same shares traded of 200 units but A has 500 restricted stocks and B has none. Using absolute share turnover will yield same turnover rate of 20% for both stocks. i.e $\frac{200}{1000} \times 100 = 20\%$. With tradable turnover, the effect of the share restriction will show that A is more liquid with 40% tradable turnover. i.e $\frac{200}{1000-500} \times 100 = 40\%$

[2] Since investors are risk averse, the hypothesis states that investors will demand a return premium above the normal expected returns for holding illiquid stocks to compensate for the risk of not being able to liquidate their position at short notice at reasonable price.

There are two main types of traders in the market; the uninformed trader and informed trader. The uninformed trader is unsophisticated and only trades for reasons (such as liquidity) other than information. Because of spontaneity and irrationality in trades of the uninformed trader, she quickly losses money and eventually leaves the market. The informed trader on the other hand is sophisticated and has access to differing levels of information about individual stocks on the market and this information is expected to trigger their trading activity. In this way, it is hypothesised that trading volume contains some information about future returns if trading on such information can generate abnormal returns.

A growing number of finance literatures offer an alternative explanation in the discourse of behavioural finance for the generally negative relationship between trading volume and expected stock returns. Baker and Stein (2004) attribute high trading volume in the prediction of lower returns to the irrational behaviour of investors of under-reaction to information flow. While this study does not focus on extreme volume-return relationship in the prediction of future stock returns, Gervais *et al.* (2001) in their study of U.S stock market show that stocks experiencing extremely high (low) volumes tend to be associated with high (low) returns. Wang and Cheng (2004) find that Chinese stocks experiencing extremely high (low) volumes tend to be associated with low (high) returns, although, this appears to contradict both the liquidity premium hypotheses and the behavioural school of thought.

The interaction between past trading volume and past returns in the determination of expected returns has featured prominently in the finance literature during the last decade. Majority of these studies have focused mainly on the US stock market. More so, stock market attributes and stock returns tend to be country-specific as suggested by Fama and French (1998). Thus it will be valuable to replicate these studies that have been done on other stock exchanges also on the OMX Helsinki. This paper is unique in that it focuses on, and perhaps the first to study, the interaction of past trading volume and past returns dynamics on contemporaneous returns exclusively on the Helsinki Stock Exchange. While the US stock market is well developed and has several stocks listed well over 5000, the Helsinki Stock Exchange is not as developed as the US stock market and the number of traded stocks is just under 250.

1.2 Research problem

This study is inspired by previous studies that examine the profitability of interaction of trading volume-return based investment strategies. The majority of these studies mainly focused on the well-developed U.S equities markets. This study is carried out in the context of the Helsinki Stock Exchange. The Helsinki Stock Exchange is a small and thinly traded market. In this paper, I examine if past trading volume – return interaction contains information about future stock returns. More importantly, I implement different trading strategies based on past trading volume – returns interaction and examine if these trading strategies generate abnormal returns on a risk adjusted basis. The methodology is based Jegadeesh and Titman (1993) portfolio formation and holding period strategy and inspired by Wang and Chin (2004) study. Using data from the Helsinki Stock Exchange, I form portfolios based on past returns and trading volume over different formation and holding periods and examine the profitability of various volume based portfolio strategies over the period from 1999 to 2010.

The results show that conditional on past returns, high-volume stocks outperform low volume stocks for most portfolio formation and holding periods. The volume discount, that is the average monthly returns difference between low volume portfolios and high-volume portfolios, is largest in magnitude for the 6 x 12 strategy for winners portfolios at -2.17% (*t*-statistics = -4.70). The results are robust to risk adjustment relative to the Fama and French (1993) three factor model. While the results obtained from this study are not entirely consistent with existing literature on the volume-return dynamics, my analysis suggests that an investor can generate superior returns by investing in portfolios of high-volume stocks and shorting portfolios of stocks with low-volume, though such trading strategy should be implemented with caution.

The remainder of this paper is organised as follows. In chapter 2, I explore related literature on market efficiency, behavioural biases, asset returns predictability and anomalies as well as discussions related to the informational role of the interaction between past trading volume and past returns as they relate to future stock returns. I present the data description and the methodology used in the study in chapter 3. In chapter 4, I present the empirical results and further explore the implications of my findings. I conclude the paper with summary and conclusion in chapter 5.

2 MARKET EFFICIENCY, TRADING VOLUME AND RETURNS

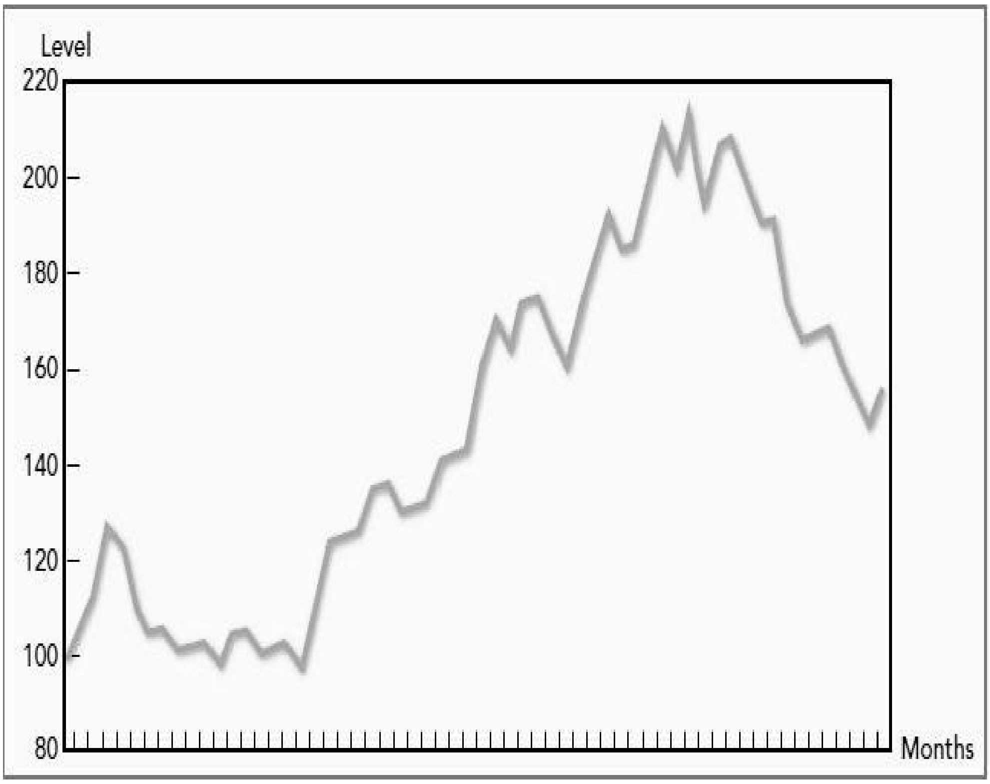
2.1 Random walk and market efficiency

One of the important hallmarks in finance is constructing a model that is able to predict future trends in stock prices, interest rates, options pricing and so on. Studies such as Errunza and Losq (1985) and Lo and MacKinlay (1988) are among the earliest body of studies that deal with the concept of stock prices predictability. A central aspect of most of these studies is the concept of random walk. The concept of random walk assumes no relationship between past and current events. With reference to stock pricing, the concept of random walk meant that observed past movement in stock prices has no influence in predicting future price path.

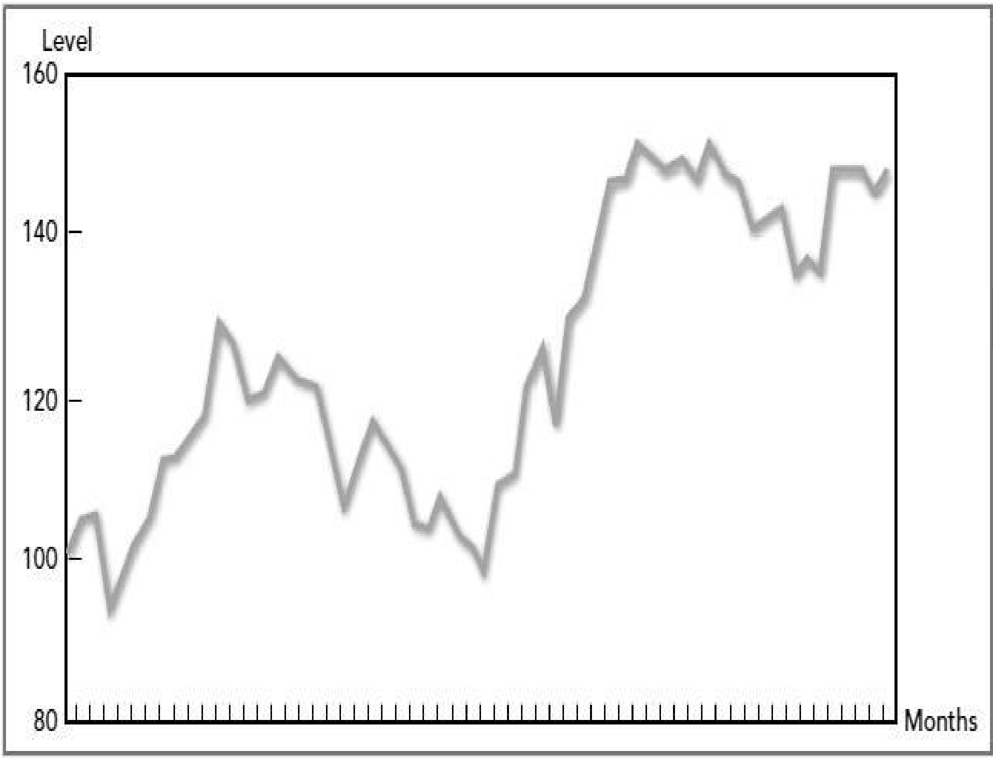
The random walk model assumes that zero correlation exists between past prices and future prices. Actual auto-correlation of stock returns is likely to be very close to zero in developed equity markets. For example, the auto-correlation co-efficient is computed for Microsoft's stock price between March 1990 and July 2001 and the result was returned as 0.022%. This means that an increase of 1% in price is likely to be followed by not more than 0.022% increase the next period. (Brealey & Myers 2003: 352.)

Two important hypotheses are central to the random walk treatment of the efficient market hypothesis; that "successive price changes are independent" and "price changes conform to some probability distribution" (Fama 1965). In other words, stock returns should be i.i.d[3] in efficient markets. In the efficient market model, independence of successive price changes means that security prices 'fully reflect' available information. These two hypotheses regarding the random walk model of stock pricing have some implications. Given that successive price changes are independent, mere knowledge of past pattern of stock prices is not sufficient in predicting future patterns of stock prices.

[3] independent and identically distributed. A sequence of random variables is said to be i.i.d if they are mutually independent of one another and comes from the same probability distribution.



Panel A



Panel B

Figure 1. Randomly Generated Fair Game for 5 Years (Panel A) and S & P 500 Index between 1980 and 1985 (Panel B) (Brealey & Myers (2003: 349))

In the Figure 1 above, a randomly generated toss of a coin for a 5-year period is shown in the Panel A. The figure reveals the fair game property of the toss as heads are likely to occur as much as tails are equally likely. The result compares quite well to the Standard and Poors 500 index between 1980 and 1985 in Panel B

Another implication of this hypothesis is that such technical analysis or chartist theorists could not do better in predicting the future pattern of stock prices. Although history might get repeated with some patterns of stock pricing, these are totally random and do not suggest some relationship between past price of stocks and the future path. Technical analysis appears to be able to identify some clear patterns of stock prices, given that at some point in time, history repeats itself with which future prices are able to be predicted. This is a far deviation from the random walk hypothesis as 'successive price changes are independent' and totally random (Fama 1965).

Kendall and Hill (1953) conclude that developing a model that perfectly depicts the behaviour of successive movements in time series data is not such an easy task and even econometric models does not appear to perform well with certainty. An important discovery in Kendal and Hill's work in developing a time series that models the behaviour of stock prices indicated that there was no visible pattern of predicting stock prices movements and that price movement are totally random. One of Kendal and Hill's conclusions centres on the predictability of stock prices. Past information on prices are not likely to have predictive capability of future price path.

Given the informational role of financial markets, to what extent is relevant available information incorporated into the pricing of securities. Fama (1965, 1970) argues that a financial market is efficient if security prices 'fully reflect' all available information. Security prices thus represent their true intrinsic value at any point in time given that all material and non-material information that has effect on such securities are fully reflected in their prices.

The concept of market efficiency is very important from the point of view of competitive markets. If investors were able to device a model which will predict stock price movements, they will be able to make riskless profits. The profits will be wiped out very soon as there are many investors willing to trade with such model and the profit opportunities will again disappear. Past information of stock prices are already reflected in the current market price and only new information can be expected to change prices. The unpredictability of such new information can be expected to make security prices changes to follow a random walk.

2.2 Behavioural finance

Traditional finance theories are based on rationality of economic agents. Rationality in this sense means two things. Firstly, agents correctly update their knowledge when new information arrives as predicted by the Bayes' rule and secondly, agents act in a consistent manner of subjective expected utility with some probability distribution. However, when agents do not act in a rational manner, then markets break down and alternative financial models are needed to explain the outcomes of individual investors' behaviours, basic facts about stock markets and the cross section of aggregate returns.

Behavioural finance[4] offers psychological based theories that seek to explain stock markets phenomena which contradict the efficient market hypothesis. Thus, the idea of informationally efficient markets whose fundamentals are expected to be incorporated into stock prices becomes irrelevant in understanding the cross section of expected returns when economic agents violates the Bayes' rule or act in a manner inconsistent with the subjective expected utility.

Most of the psychological based theories in behavioural finance are anchored on the works of Kahneman and Tversky (1992, 1979) and Thaler *et al.* (1997). Their works have had practical implications in understanding the cross section of expected returns and the behaviour of individual investors in the stock market. For example, Grinblatt and Han (2005) have shown that prospect theory and mental accounting of Kahneman and Tversky (1979) can create positive and significant relationship between capital gains overhang and future returns. By controlling for the capital gains overhang, profitable momentum strategy largely dissipates.

[4] For an extensive review of behavioural biases that have been documented in the financial literature, see Shleifer (2000) and Thaler (2005).

Based on a time series of monthly returns and turnover, Statman *et al.* (2006) have also shown that individual and market wide turnover is positively related to lagged security returns and market wide returns and interpreted this as a sign of investors' overconfidence. Grinblatt and Keloharju (2009) also show that a model of investor behaviour based on over-confidence and sensation seeking can explain investors' excessive trading in equities market.

2.3 Stock returns predictability and anomalies

In much of the past half century, stock returns were thought of to be no more than random walks. Returns were unpredictable. Recent developments in Finance have however documented variables that have predictive capabilities over asset returns. One of the famous examples of variables that have predictive powers is the book/market ratio which Fama and French (1993) show that stocks with low market value relative to their book value outperform stocks with high market value relative to their book value. We now have models that predict between short-term returns of three months to twelve month (Jegadeesh & Titman 1993) to longer horizon returns of three to five years (Lee & Swaminathan 2000).

Empirical evidences show that there are stock market factors that can and do forecast returns, for example, Cochrane (2008) shows that the dividend-price ratios do forecast long-horizon returns. Other variables also include past sales growth, past returns, liquidity measures such as past trading volume earnings announcement; the list is numerous. In fact, the research on return predictability and the appearance of forecasting variables in the financial literature can be best summarised when Lettau and Ludvigson (2001: 842) wrote that "it is now widely accepted that excess returns are predictable by variables such as dividend-price ratios, earnings-price ratio, dividend-price ratios, and an assortment of other financial indicators".

The research on asset pricing has been very extensive. More than fifty variables have been shown to have predictive powers for asset returns but as Subrahmanyam (2010) pointed out, more needs to be done in the areas of correlation amongst the variables and more rigorous methodology to ensure that the results are robust across different methodologies and with different data. More so, most of the predictability in asset returns are likely due to data snooping and methodological issues which was suggested by Fama (1998) as most of the anomalies are chance results and do survive with rigorous change of technique. Yet, other researchers have found that some of the variables forecasting returns perform poorly on in-sample and out-of-sample data. For example, Welch and Goyal (2008) show that asset returns forecast that is based on dividend yields and a host of other variables do not pass when applied on out of sample data. Nonetheless, a discerning critic of returns predictability should not be too eager to conclude that returns forecastibility is dead neither. As pointed out in Cochrane (2005: 12), “there is still not a shred of evidence that price ratios forecast dividend growth. If prices vary, they must forecast something—we cannot hold the view that both returns and dividend growth are i.i.d. Thus, the lack of dividend forecastibility is important evidence for return forecastibility, and this is ignored in the statistical studies”.

While the CAPM contends theoretically that the returns on a stock or a portfolio are determined by the assets exposure to the market portfolio, new evidences have proved otherwise that the CAPM cannot fully explain the cross section of stock returns. Because of the deviations of stock returns from the CAPM, Fama and French (1996) referred to these factors as anomalies. In this section, I briefly survey some of the important factors that have explanatory significance in forecasting stock returns. The following sub-sections provide a quick overview of the important factors that are relevant to this paper.

2.3.1 Liquidity and trading volume

The effects of stock market liquidity on asset returns have been well explored in the financial literature. Liu (2006: 631) defined liquidity as “the ability to trade large quantities quickly at low cost with little price impact”. In their classical paper on asset pricing and liquidity, Amihud and Mendelson (1986) use securities’ bid-ask spread as a proxy for liquidity to study the effect of illiquidity on the assets’ returns. They document that stocks’ return volatility is positively correlated with contemporaneous trading volume. Other researchers have found the bid-ask spread to be negatively correlated with other liquidity measures including trading volume, see Stoll (2002). Most liquidity measures have focused on trading volume, speed, cost and the price impact as suggested in Liu (2006).

Karpoff (1987) also provides a synthesis of earlier studies that relates trading volume to price changes. He summarized his findings into two stylized facts from the empirical studies relating trading volume to price changes. He noted particularly that the correlation between trading volume and the absolute price change is positive in both futures and equities market and that the correlation between trading volume and contemporaneous price changes in equities market is positive. Still on the volume – return relation, Gallant *et al.* 1992 find that high trading volume is preceded by large price changes and while conditioning on lagged volume, a positive risk-return relation exists.

Papers such as Chordia and Swaminathan (2000) and Llorente *et al.* (2002) have also examined the trading volume – return dynamics. The discourse on volume – return relationship has not only centred on volume granger cause return relationship as Statman *et al.* (2006) find that over short horizons of six months, contemporaneous market-wide returns do predict subsequent higher trading volume. Although, the notion that trading volume contains some relevant information about future stock returns has existed for so long, the extent of such information was largely unknown until the recent past decade.

There are basically two dimensions to understanding the discourse on the trading volume – asset prices relationship; a market efficiency based explanation and a behavioural dimension. In efficient markets, it is not possible to earn an abnormal profit on a risk adjusted basis by trading on past and publicly available information. It appears that a violation of efficient markets hypothesis might exist in the possibility of past trading volume to predict contemporaneous returns. For example, Datar *et al.* (1998) used share turnover rate to proxy for the bid-ask spread in Amihud and Mendelson (1986) and find further support for the liquidity premium. Thus, the observed premium in asset returns as a result of lagged trading activity is not a violation of the efficient markets but a compensation for holding illiquid assets. As rightly pointed out in Amihud and Mendelson (1986) and further corroborated by Pástor and Stambaugh (2003), investors that face a higher liquidity constraint during liquidation of their assets would require higher expected returns.

As mentioned earlier in the preceding section, several anomalies have been shown to contradict established finance theories. A model of investor overconfidence in behavioural finance has also been shown to explain investors' over-weighing of their private information in generating excessive trading volume. High volume stocks that catch investors' attentions have also shown to be characterised with high volume-return premium relationship in US equity market (Gervais *et al*. 2001) and also in cross country data (Kaniel *et al.* 2012). The disposition effect in Grinblatt and Han (2005) also shows that investors will tend to trade less actively when their investments have lost much in value and trade more when their investment have appreciated more in value. Also noise traders who trade for reasons other than liquidity and rationality have also been shown to influence the level of trading activity and subsequently stock returns.

2.3.2 Momentum

The tendency of past winner stocks to appreciate in value while past loser stocks continue to decline in value is termed momentum in the financial literature. In contrast to the efficient markets hypothesis, Jegadeesh and Titman (1993) show that buying past winners and selling past losers generates an abnormal profit for the US equity markets of up to 12% per annum. They find that the abnormal profits are not related to systematic risks of winner stocks being any riskier than loser stocks. If winner stocks are characterised by small firm size compared to loser stocks, their higher returns could be due to size effect in Banz (1981). However, Jegadeesh and Titman 1993) find that loser stocks on the contrary have lower average market capitalization than winner stocks. Also, they find that the beta, which measures the stocks' sensitivity to the market portfolio, for loser stocks is higher than the beta of winners stocks. This abnormal profit in momentum strategy has not been shown to be captured by the paradigm capital asset pricing model.

International evidence on momentum is although mixed, there are a number of published papers supporting the profitability of momentum strategies in international stock markets. For example, in an analysis of twelve European countries, Rouwenhorst (1998) finds that a momentum strategy that invests in past winners and sells past losers earn about 1% per month which is statistically significant for all countries analysed except for Sweden. Also, Griffin *et al.* (2003) find that statistically and economically significant momentum profits exist in international data. See also Chui *et al.* 2010), Fama and French (2012), Novy-Marx (2012) and Asness *et al.* (2013).

Since the publication of Jegadeesh and Titman (1993) paper on price momentum, several other authors have documented the pervasiveness of profitable momentum strategy that buys past winner stocks and sell past loser stocks which outperform a buy-and-hold strategy. They suggest that a model of investor's under-reaction to short-term information can explain profitable momentum strategies. Attempts at explaining this momentum profits have largely followed a behavioural finance path. For example, Barberis *et al.* (1998), Hong and Stein (1999) attribute the profitable momentum strategies to investors' overconfidence, conservatism and under-reaction to information. This behavioural explanation for the continuation of momentum profits was further corroborated in Jegadeesh and Titman (2001) using an extended out-of-sample data. Asem (2009) also shows that dividend policies can affect momentum profits. He shows that buying winners that have increased their dividends and shorting losers that have decreased their dividends enhances momentum profits which is consistent with other behavioural models of investors' under-reaction to news flow.

An alternative to behavioural finance explanation to momentum profits has also featured in the financial literature. Profitable momentum strategies do not necessarily arise as a result of investors' under-reaction to information as Johnson (2002: 585) finds that a simple "model of firm cash-flows discounted by an ordinary price kernel can deliver a strong positive correlation between past realized returns and current expected returns" The emphasis here is that momentum profits can be understood in terms of firm specific time varying risk characteristics as opposed to investors under-reaction to information or other behavioural biases. Liu and Zhang (2011) also attribute profitable momentum strategies to market efficiency when they link the profits to economic fundamentals driving stock returns.

Chan *et al.* (1999) while confirming the profitability of momentum strategies also point out that chasing these strategies could generate higher transaction costs, although their conclusion falls under investor under-reaction to information. Other risk-based characteristics that have been shown to explain momentum profits include distress risk in Eisdorfer (2008) and Agarwal and Taffler (2008), credit risk in Avramov *et al.* (2007). In spite of the advances at understanding the source of momentum profits, there has not been a convergence among scholars

2.3.3 Size

Banz (1981) was the first to document the "size effect" in the cross section of returns in the US equity markets. Size effect refers to the tendency for small market capitalization stocks to outperform large capitalization stocks on a risk adjusted basis. Banz (1981) documents that the portfolio of the bottom 20% small stocks have outperformed the rest of the stocks by an average of 0.4% per month over the period from 1936 to 1977 and that this persistent return is significant in both statistical and economic terms. This finding contradicts the CAPM that the return on a security is linearly related to the stock's non-diversifiable risk represented by the market beta.

More evidences that document that the size effect is a risk factor that is not captured by the CAPM abound in the financial literature. A size factor, included in Fama and French (1993) three factor model, was found to be statistically significant in explaining the cross section of stock returns. Most academics now use a multifactor variant of the CAPM which usually include a size factor to explain the cross section of asset returns. For example, Carhart (1997) includes a size factor in their four factor model to evaluate the performance of mutual funds. Fung and Hsieh (2004) also add a size factor in their seven factor model to explain the returns of hedge funds.

The size effect has received tremendous attention from researchers seeking to understand what drives the cross section of stock returns. Hawawini and Kleim (2000) extend the research on the size effect by providing a synthesis of the size effect across numerous stock markets around the world. While realising the fact that the size effect does exist in the international equities market, they posit that the premium is either a compensation for the risk or an evidence of an inefficient market.

Despite the popularity of the use of multi-factor models to explain the cross section asset returns, some researchers have documented some methodological and data snooping bias in the use of size factor as an explanatory factor in the cross section of asset returns. Yet, others conclude that the size effect does not just exist. For example, Horowitz *et al.* (2000) posit that the use of size factor in asset pricing studies is unnecessary when they found no systematic relationship between expected return and firm size in a study of NYSE, AMEX and NASDAQ stocks over the period 1980 – 1996. Van-Dijk (2011) provides more than 30 years of review on the size effect and, while acknowledging varying levels of theoretical and empirical deficiencies in the use of size factor, concludes that size is not dead.

2.3.4 Value

Value is another so-called anomaly that has been shown to deviate from the standard capital asset pricing model. At its basic form, value investing involves buying assets that are cheap relative to their fundamental valuation and shorting stocks that are rich relative to their fair fundamental values. Although, there is not a single generally accepted indicator of the fair fundamental value of a stock, academics and practitioners have used different kinds of financial ratios relative to the market price to form the value factor. Common among the value factors include low price-to-book ratios (P/B), low price-to-earnings ratio (P/E), high dividend yield (D/P) and high free cash flow yield (FCF/P). Growth stocks is the opposite of value stocks, i.e. growth stocks are characterised by high price relative to some fundamental fair values such as high price-to-book ratios, high price-to-earnings ratio, low dividend yield and low free cash flow yield.

There is evidence in the financial literature that value stocks as defined above outperform growth stocks. The profitability of value investing has been documented in De Bondt and Thaler (1985) using the price-to-earnings ratio, Fama and French (1992, 1993) using the price-to-book ratio, Bird and Whitaker (2003) using the dividend yield. Chan *et al.* (1991) find that the free cash flow yield and the price-to-book market ratios have very significant positive impact on expected returns. These results are not only prevalent with U.S data but also present in international data. For example, Asness *et al.* (2013) while examining the value and momentum premia using global market indices find that both value and momentum premia are present in eight diverse markets as well as across different asset classes including equity indices, bonds, currencies and commodity futures. See also Cakici *et al.* (2013).

Attempts at understanding the value premium have largely followed one of two dimensions as in the case of other anomalies; a risk based explanation and a behavioural finance path. Following a risk-based explanation, Fama and French (1993) argue that the value factor in their three factor model is a proxy for distress risk. Alternatively, Lakonishok *et al.* (1994) presents a behavioural finance model where investors’ extrapolation of past earnings can explain profitable value strategies and not because value stocks are fundamentally riskier. Yet, other academics have taken the view that these two conflicting explanations can be complementary as argued in Chaves *et al.* (2012).

2.4 The informational content of trading volume

The financial literature contains several stylised facts about the informational role of trading volume and other liquidity measures. The magnitude of trading volume observed in the stock market can be a function of the heterogeneity of information endowment of different investors. As aptly summarised in Karpoff (1987: 109), the "rate of information flow to the market, how the information is disseminated, the extent to which market prices convey the information, the size of the market . . ." can provide valuable insight to understanding the price – volume relationship.

Epps (1975) provides a simple model where there are two types of investors in the stock market – the bull trader and the bear trader – each with its own sets of beliefs and information endowment. The bull trader reacts only to positive information about the underlying asset and is more optimistic about the value of the asset at the end of the trading period. The bear trader on the other hand reacts only to negative information about the asset and is more pessimistic. The interaction of the sentiments between these two groups of investors in the market thus generates the trading volume in the market as the bulls are net buyers while the bears are net suppliers. Although, the validity of this model has been questioned as the bears will ultimately hold negative positions, it nonetheless provides an understanding of the structure of the stock market.

He and Wang (1995) also develop a model of stock trading that relates the amount of private information flow to investors' trading volume. While volume may be related to non-informational induced trading such as supply shocks, they find that "the pattern of volume is closely related to the flow and nature of information" in the market. The use of trading volume to proxy for the amount of information flow has also been extensively used in the financial literature. For example, Baker and Stein (2004) show that high trading volume can be an indicator of the presence of irrational traders who underreact to information flow. Tetlock (2007) also analysed the role of media in the stock market and finds that unusually high or low pessimism can predict high market trading volume consistent with models of noise and liquidity trading.

Two main types of traders feature prominently in the market; the informed trader who trades based on private information and the uninformed or noise trader who trades based on other reasons such as liquidity needs. In the model developed in Suominen (2001), these two types of traders act in a competitive way to determine equilibrium prices in the stock market. At equilibrium, the informed traders compete with liquidity traders and after a while, the amount of private information being held by the informed traders eventually dissipates into the market. The result in the model is consistent with earlier empirical work that there exist a positive correlation between price change and trading volume. See also Blume *et al.* (1994).

2.5 Evidence on volume level and expected returns

The foregoing discourse relates several stylised facts about return predictability and volume level. In this section, I present a synthesis of earlier empirical studies on the volume – return relationship. First, there is strong evidence in the U.S that relates trading volume to stock returns. It is important to note that measures such as dollar trading volume which is the absolute number of shares traded and share turnover defined as the number of shares traded by the number of shares outstanding of that stock has been used as proxies for trading volume. Most of the studies document a generally negative relationship between trading volume measures and expected returns. Similar results were also obtained using international data. While most of these results support the theoretical explanation that liquidity is a priced factor in the stock market consistent with market efficient theory, there are a couple of papers that relate the phenomenon to behavioural biases. Although, some of the empirical evidences have surfaced in the preceding sections, I highlight some of the prominent studies that relate trading volume level (proxied by different liquidity measures) and expected returns in table 1.

First, consistent with Amihud and Mendelson (1986) liquidity premium hypothesis, Datar *et al.* (1998) find that turnover rate is negatively related to stock returns in a sample of NYSE stocks during the period 1962 - 1991. Their result is robust even after controlling for common stock market factors such as book-to-market ratio, firm size, market beta and

January effect. They use the Fama-Macbeth type regression based on the GLS regression to examine the impact of turnover rate on the cross section of stock returns. They regress monthly stock returns on firm characteristics such as turnover, book-to-market ratio, firm size and firm beta.

Table 1. Selected studies on the volume- return relationship

Authour(s)	Stock market	Volume measure	Lagged Volume – return relationship
Datar *et al.* (1998)	NYSE	Share turnover	Negative
Brennan *et al.* (1998)		Dollar volume and share turnover	Negative
Rouwenhorst (1999)	20 emerging markets	Share turnover	No relationship
Lee and Swaminathan (2000)	AMEX/NYSE	Share turnover	Negative
Chordia *et al.* (2001)	AMEX/NYSE	Dollar volume and share turnover	Negative
Wang and Chin (2004)	Shanghai and Shenzhen	Share turnover	Negative
Wang and Cheng (2004)	Shanghai and Shenzhen	Dollar volume	Negative
(Gębka 2008)	Warsaw	Dollar volume	Negative

In a similar approach, Chordia *et al.* (2001) find statistically significant negative relationship between average returns and trading volume proxied by dollar volume and share turnover. In their time series regression, they find that average median returns decline within each quintile portfolio as they move from low trading volume to high trading volume. Their result holds after various robustness checks.

After forming portfolios based on different formation periods of 3, 6, 9 and 12 months and held for same holding period, Lee and Swaminathan (2000) show that portfolios with low past turnover rate outperform portfolios of high turnover rate in a sample of NYSE/AMEX stocks between 1965 and 1995. Their results holds also within sub-samples and by also leaving a one-month lag between formation period and beginning of holding period to account for possible microstructure effects. Their results also do not appear to be influenced by common stock market factors after controlling for the Fama and French (1993) size and value effect.

Based on data from 20 emerging markets, Rouwenhorst (1999) finds no significant difference between average returns of portfolios formed on the basis of ranking their lagged period turnover to the extent that return on high turnover portfolios exceed that of low turnover portfolios in 12 out of the 20 markets. In Chinese stock market, Wang and Chin (2004) and Wang and Cheng (2004) both find negative relationship between share turnover and expected returns.

3 DATA AND METHODOLOGY

In this chapter, I provide an in-depth explanation of the methodology used to analyse the profitability of volume-based portfolio strategies. In the first section, I provide the data description and some summary statistics of the sample used. The methodology and model used in the empirical study are introduced in the latter part of the chapter.

3.1 Data description

This study utilizes monthly data of all stocks listed on the OMX Helsinki Stock Exchange[5]. The raw data is from December 31, 1999 to December 31, 2010 and comprises all stocks that have information on daily stock returns, market capitalization, daily trading turnover, and daily market returns. Stocks with missing data points on some trading days are excluded from the sample for the given period. Finally, to be included in the sample, a stock must be traded for at least a day in each of seven consecutive months at the minimum. The reason for this is that the methodology used in the study requires at least three month formation period and three month holding period with a one month lag between end of formation period and beginning of holding period. The stock returns are calculated from the total return index which already accounts for dividends and stock splits. Thus, the return used in this study is the total returns an investor would be expected to earn for a buy and hold strategy. Also, instead of using the return index at either the beginning or the end of the month, the daily returns are cumulated into monthly returns in order to form portfolios of three, six, nine and twelve month stock returns and trading turnover. Again, these monthly returns takes into account the total returns and investor would be expected to earn within a given month.

Trading turnover as used in this study is defined as the ratio of shares traded in a month divided by the total shares outstanding. Wang and Chin (2004) argues that the use of tradable turnover as opposed to pure trading turnover eliminates distortions arising from ownership structure and restricted shares which are not allowed to be traded. Nonetheless, due to the unavailability of data on ownership structures and restricted shares, this study

[5] I am grateful to Prof. Jukka Pertunen and Prof. Hannu Kahra for providing me with the raw data use in this study.

utilizes the use of trading turnover rather than tradable turnover. The final data used in this study comprises a total of 248 shares spread throughout the sample period. Table 2 presents some summary statistics about the sample.

Table 2. Summary Statistics of the sample

	No. of Stocks	Market Cap (bn€)	Mean Monthly Returns (%)	Mean Monthly Turnover (%)
1999	183	347.99	3.02	0.20
2000	188	317.15	0.23	0.18
2001	181	218.73	0.27	0.15
2002	174	158.59	-0.54	0.14
2003	168	159.69	5.33	0.17
2004	163	159.97	1.58	0.19
2005	160	203.35	2.34	0.27
2006	161	237.05	1.68	0.27
2007	154	280.64	0.07	0.30
2008	149	130.16	-4.66	0.22
2009	144	162.27	3.59	0.19
2010	140	192.53	1.46	0.17

The table reports for each sample year the number of stocks traded throughout the fiscal year, market capitalization as at the last date of the trading day in the year, the average monthly turnover and the mean monthly returns. The maximum number of shares traded peaks in 2000 which also reflects the general technology boom in Finnish stock market and the global stock market. Since 2001, there has been a steady decline in the number of shares and the lowest number of shares in the sample is recorded at the end of sample period. The Finnish stock market is also not immune from shocks in the global equities market with the decline in market capitalization by nearly 46% in 2008 before gradually recovering in 2009 and 2010. At the same time, returns were also negative and mean monthly trading turnover were generally less than 1% during the sample period.

It is important to note that the trading turnover rate in the sample ranges between 0.000045% and 37.85% and has a mean of 0.20% in the initial sample. Since there is a large variability in the turnover rate, it is likely that results may be driven by a few extreme observations. Therefore, I eliminate the top and bottom 1% observations from the sample and re-estimate the profitability of volume-based portfolios. In the trimmed dataset, the turnover rate varies from 0.0020% to 1.398% and has a mean of 0.175%. The results from the initial and trimmed dataset are presented in section 4.1. In contrast to other stock markets, the trading turnover on the Helsinki Stock Exchange is exceptionally low. For example, Datar *et al.* (1998) finds that the trading turnover usually ranges from 0.0013% to 110% with a mean of 3.6% in a sample of NYSE stocks. Lee and Swaminathan (2000) documents an average of 4.2% monthly trading turnover also for the NYSE while in the Chinese stock market, Wang and Chin (2004) finds that trading turnover ranges between 9.45% and 34.2%. One possible reason for this low trading turnover is likely due to the small market size and the thinly traded nature of the exchange.

3.2 Methodology

The methodology used in this study is based on Jegadeesh and Titman (1993) portfolio formation and holding period strategy and inspired by Lee and Swaminathan (2000) and Wang and Chin (2004) studies. As outlined in chapter one of this text, this paper intends to examine if the interaction of past stock returns and trading volume contains information on contemporaneous returns and, if any, whether this information can be used in trading strategies that are able to generate abnormal returns on a risk adjusted basis. I believe the methodology of Jegadeesh and Titman (1993) and that of Wang and Chin (2004) is most appropriate for this study since the latter were looking into profitability of volume based momentum portfolios within a short period. My study follows similar path with only 12 years of data.

Based on the methodology, the portfolios are formed on the basis of the interaction of past stock returns and past trading turnover. In doing this, all stocks are first sorted into three equal size portfolios based on the past J month's return and the position is then held for the next K months where J, K = 3, 6, 9 and 12[6]. Portfolio formation starts in April 1999 because three months formation period is needed at the minimum and one month skipped period between portfolio formations and beginning of holding period. I use overlapping observations at one month intervals and the portfolios are rebalanced every month. In addition, the stocks are also independently ranked on the basis of the past J month's trading turnover and held for the next K months where J, K = 3, 6, 9 and 12 . The two independent sorts are combined together to form a two-way sorted portfolio that has intersection of both past stock returns and past trading turnover. Thus, P_1 denotes the tertile

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[6] Except otherwise explicitly stated in this text, J,K = 3, 6, 9 and 12.

portfolio of loser stocks and P_3 denotes the tertile portfolio of winner stocks. Similarly, V_1 denotes the tertile portfolio of lowest trading turnover stocks and V_3 denotes the tertile portfolio of stocks with the highest trading turnover. Therefore, P_3V_3 represents the portfolios of high volume winners and P_1V_1 represents the portfolio of low volume losers. Similarly, P_3V_1 represents the portfolio of low volume winners and P_1V_3 represents the portfolio of high volume losers. Thus, the universe of the portfolios consists of 2-way sorted portfolios[7] for a total of 9 portfolios of the interaction between the past *J* month's return and past *J* month's trading volume.

3.3.1 Portfolio formation procedure

Following the methodology of Jegadeesh and Titman (1993), the actual portfolios formation procedure proceeds as follows. The monthly returns for all stocks are cumulated for the past *J* month formation period. For example, the *J*-month period cumulative return is computed as follows:

$$R_{c,J} = (1 + R_1)(1 + R_2)\ldots\left(1 + R_J\right) - 1 \qquad (1)$$

$where$

$R_{c,J} = J\ month\ cummulative\ returns$

$R_1, R_2 \ldots\ R_J = 1, 2 \ldots\ to\ J\ months\ prior\ to\ portfolio\ formation$

This process is repeated for all the portfolio formation period. Next, the stocks are ranked on the basis of their past *J* month's returns into three equal size portfolios of winner portfolios, middle portfolios and loser portfolios. Only the extreme portfolios are considered in this paper, i.e, winner and loser portfolios. The returns of each portfolio are equally weighted returns.

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[7] 9-way sorted portfolios

	P_1	P_2	P_3
V_1	1	2	3
V_2	4	5	6
V_3	7	8	9

Following same procedure as above, each tertile portfolios formed on the basis of the past *J* month cumulative returns are also independently ranked on the basis of their past *J* month cumulative trading turnover. Therefore, for the winner portfolios, the stocks are ranked into three portfolios such as high volume winner portfolios, mid-volume winner portfolios and low-volume winner portfolios. Similarly, the loser portfolios are sorted into high-volume loser portfolios, mid-volume loser portfolios and low volume loser portfolios. For example, the cumulative trading turnover for the 3-month portfolio formation period for both winner and loser portfolios are computed as follows:

$$V_{3,t} = V_{t-1} + V_{t-2} + V_{t-3} \tag{2}$$

$where$

$V_{3,t} = cumulative\ turnover\ for\ 3 - month\ formation\ period\ at\ time\ t$

$V_{t-1}, V_{t-2}, V_{t-3} = monthly\ turnover\ for\ 3\ periods\ before\ formation\ period$

The equations *(1)* and *(2)* above are repeated for all portfolio formation periods 3, 6, 9 and 12 month. Recall that the intersection of the two independent sorts of the interaction between past trading turnover and returns will result into 2-way sorted portfolios consisting of 9 portfolios. I focus only on the extreme portfolios.

Each of the extreme portfolios from the 2-way sorted portfolio is then held for the next *K* month holding period where *K* is as defined earlier. The portfolios are rebalanced in the manner specified in Jegadeesh and Titman (1993). Specifically at the end of every month *t*, each portfolio is rebalanced by liquidating *1/K* of the holdings and reinvested into new high volume portfolios or low volume portfolios based on the new past *J* month cumulative trading turnover while the rests of the holdings are carried forward to the following period. The procedure is repeated for every month for each of the *K* holding periods. Thus, by combining different portfolio formation period and holding period on the basis of past *J, K* months, one gets a total of 16 trading strategies for each of the high and low volume winners as well as high and low volume losers portfolios.

3.3.2 Portfolio performance evaluation procedure

In this section, the portfolio performance evaluation procedure is presented. Using the method of Jegadeesh and Titman (1993), the portfolio performance evaluation for the 3-month formation period and held for 3 months is presented as follows. The same procedure is true for all other *J, K* strategies. The return data are aggregated at the end of every month so that the entire total return index for that month is taken into consideration. For example, for the initial three month formation period in 1999, the dates are as follows: January 29, February 26 and March 31.

So, let us assume that the three month formation period has started on January 29 to end on March 31. The first formation date will be April 30 and the first performance period evaluation period is May 31. The reason for this one month lag between end of formation period and beginning of holding period is to avoid some of the market microstructure effects such as the bid-ask bounce, price pressure that has been documented in the financial literature. For example, Conrad and Kaul (1993) have argued that a spurious result can occur whenever a single period return is cumulated over a period of time due to the bid-ask bounce and non-synchronous trading. They argue that this spurious result is most pronounced in illiquid markets. One can categorise the Helsinki Stock Exchange as one that is highly illiquid when compared to other stock markets. By skipping one period between portfolio formation period and performance evaluation period, one can avoid some of the bid-ask errors, see Jegadeesh and Titman (1993).

The portfolios formed in the three month period above are evaluated throughout May, June and July. Thus for each month t, the strategy closes out a position initiated in month *t-k* and the weight are revised on *1/k* of the stocks in each portfolio. The return on the basis of the *1/k* of the portfolio can be labelled *simple portfolio returns* and the returns for the whole of the *k*-month holding period can be labelled *composite portfolio returns*. The composite portfolio returns are simply the arithmetic means of the simple portfolio returns. By using this simple monthly rebalancing to compute the composite portfolio returns on the basis of simple portfolio returns allows one to use the simple *t*-statistics to evaluate the significance of the composite portfolio returns.

For brevity and clarity, I illustrate the foregoing explanation with simple notations as follows:

$$R_{May} = R_{JFM} \tag{3}$$

$where$

$R_{May} = return\ on\ composite\ portfolio\ for\ high\ volume\ winner\ portfolio\ in\ May$

$R_{JFM} = return\ on\ simple\ high\ volume\ winner\ portfolios\ for\ Jan, Feb\ \&\ March$

After one month, the composite return for the high-volume winner portfolios for June is computed as follows:

$$R_{June} = \frac{2}{3}R_{JFM} + \frac{1}{3}R_{FMA} \tag{4}$$

$where$

$R_{June} = return\ on\ composite\ portfolio\ for\ high\ volume\ winner\ portfolio\ in\ June$

$R_{JFM} = return\ on\ simple\ high\ volume\ winner\ portfolios\ for\ Jan, Feb\ \&\ March$

$R_{FMA} = return\ on\ simple\ high\ volume\ winner\ portfolios\ for\ Feb, Mar\ \&\ April$

The first full 3-month performance evaluation period is in July and the composite return for that month is computed as follows:

$$R_{July} = \frac{1}{3}R_{JFM} + \frac{1}{3}R_{FMA} + \frac{1}{3}R_{MAM} \tag{5}$$

$where$

$R_{July} = return\ on\ composite\ portfolio\ for\ high\ volume\ winner\ portfolio\ in\ July$

$R_{JFM} = return\ on\ simple\ high\ volume\ winner\ portfolios\ for\ Jan, Feb\ \&\ March$

$$R_{FMA} = return\ on\ simple\ high\ volume\ winner\ portfolios\ for\ Feb, Mar\ \&\ April$$

$$R_{MAM} = return\ on\ simple\ high\ volume\ winner\ portfolios\ for\ Mar, Apr\ \&\ May$$

Table 3 below reports some descriptive statistics for the two independent sorted portfolios. Some returns pattern is visible from the table. Generally, the returns from the winner portfolios denoted by P_3 for both low volume and high volume stocks are positive and generally higher than the returns of the loser portfolios, P_1, for all portfolio formation periods except for the 9- and 12-month high volume winners. Turnover is generally below 1% in each holding period with high-volume portfolios reporting almost four times the turnover of low volume portfolios

Table 3. Descriptive statistics of the extreme two independent sorted portfolios

		V_1			V_3		
		Return		Turnover	Return		Turnover
J	Portfolio	Mean	SD		Mean	SD	
3	P_1	0.83	12.54	0.07	0.68	18.45	0.40
	P_3	1.12	28.22	0.10	2.63	70.52	0.41
6	P_1	0.86	13.08	0.07	0.71	18.52	0.39
	P_3	0.69	10.20	0.10	2.71	71.77	0.39
9	P_1	0.87	12.14	0.06	1.97	74.48	0.40
	P_3	1.15	11.01	0.09	1.59	13.13	0.38
12	P_1	0.80	13.26	0.06	1.71	74.92	0.39
	P_3	0.84	9.59	0.10	0.98	12.41	0.37

The reported figures are in percentages. Mean return is the average monthly returns over the period 1999 to 2010 for different portfolio formation period represented by *J* where *J* equals 3, 6, 9 and 12 months. SD is the standard deviation of the returns. V_1 and V_3 represent portfolios of low- and high-trading volume. P_1 and P_3 is the portfolio of loser and winner stocks.

3.4 The Model

The goal of this thesis is to examine if past trading volume-return interaction contains information about future returns. Specifically, I examine if a trading strategy based on past trading volume-returns interaction generates excess returns on a risk adjusted basis. The strategy used in this study invests in portfolios of low-volume stocks and shorts portfolios of high-volume stocks.

First if past trading volume-return interaction contains information about future stock returns, a trading strategy based on this interaction should be able to predict future stock returns. Secondly, the trading strategy should be profitable relative to common stock market factors. To test whether this trading strategy is profitable, the following model is used:

$$P_{1,3}V_1 - P_{1,3}V_3 = 0 \quad (6)$$

where

$P_{1,3}V_1 = portfolios\ of\ losers(winners)\ low\ volume\ stocks$

$P_{1,3}V_3 = portfolios\ of\ losers(winners)\ high\ volume\ stocks$

There should be a statistical significant difference between the two portfolios shown above if the interaction of the returns and volume data contains information about future stock returns. Rational liquidity hypothesis is consistent (Amihud & Mendelson 1986) clientele effect evidence that illiquidity is consistent with higher expected returns. Thus, a trading strategy based on equation 6 should be non-zero and statistically positive.

Previous studies are also consistent with the rational liquidity hypothesis that illiquid stocks provide higher expected returns. On the contrary, this study finds that portfolios of more liquid stocks provide higher expected returns. The results documented in this study may be due to the special nature of the Finnish stock market. See section 4.1 and chapter 5 for further comments on the results

4 EMPIRICAL WORK

The results from the methodology discussion and model specification are presented in this chapter. The first part of this chapter reports the composite portfolio returns as well as their *t*-statistics for the 16 trading strategies for the different portfolios discussed in section 3.2. The second part of the chapter reports the results from the risk-adjustment relative to the Fama and French (1993) three factor model to account for the effects of common risk factors in stock markets.

4.1 Results

The main results of my empirical work are presented in table 4. Table 4 reports the composite portfolio returns in percentages and their *t*-statistics for the 16 trading strategies for the low-volume loser portfolios, high-volume losers, low volume winner portfolios, and high volume winner portfolios as well as their volume discounts for both loser and winner portfolios.

Panel A of the table reports the average monthly returns for the whole sample and Panel B reports the average monthly returns after excluding the top and bottom 1% extreme observations to adjust for outliers. Despite this adjustment, the returns for both panels in table 4 closely follow each other. The results from the table are somewhat mixed. First, the returns for all portfolio formation and holding period for both low- and high-volume portfolios are all positive. For the 3- and 6-month formation period, winner portfolios outperform loser portfolios for most holding periods but for few exceptions. Similarly the 9- and 12-month formation period returns for high volume losers outperform low volume losers portfolios while for the same formation periods, low volume winners outperform low volume losers. Also the statistical significance of the results does not follow one particular order.

The average monthly returns for volume discount portfolios (V_1-V_3) are negative for most holding periods but for few exceptions. These exceptions are not statistically significant. The volume discount return is largest at -2.17% for the 6 x 12 month strategy for winner portfolios and also highly statistically significant.

Table 4. Panel A: Returns on volume-based 2-way sorted portfolios

J \ K		3			6			9			12		
		V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3
3	P_1	0.88	0.69	0.19	0.92	0.70	0.22	0.91	0.73	0.18	0.92	0.73	0.18
		(2.68)	*(1.22)*	*(0.47)*	*(3.60)*	*(1.66)*	*(0.77)*	*(4.24)*	*(2.11)*	*(0.78)*	*(4.95)*	*(2.43)*	*(0.90)*
	P_3	1.09	2.74	-1.65	1.10	2.77	-1.66	1.11	2.80	-1.69	1.15	2.83	-1.69
		(2.19)	*(2.83)*	*(-1.78)*	*(3.06)*	*(4.03)*	*(-2.54)*	*(3.82)*	*(4.81)*	*(-3.02)*	*(4.63)*	*(5.56)*	*(-3.43)*
6	P_1	0.88	0.75	0.09	0.82	0.70	0.12	0.79	0.74	0.05	0.76	0.76	-0.01
		(2.57)	*(1.32)*	*(0.23)*	*(3.26)*	*(1.66)*	*(0.39)*	*(3.78)*	*(2.09)*	*(0.17)*	*(4.24)*	*(2.42)*	*(-0.03)*
	P_3	0.65	2.75	-2.10	0.62	2.66	-2.05	0.62	2.71	-2.09	0.62	2.78	-2.17
		(2.45)	*(2.74)*	*(-2.27)*	*(3.07)*	*(3.76)*	*(-3.22)*	*(3.52)*	*(4.51)*	*(-3.97)*	*(3.87)*	*(5.25)*	*(-4.70)*
9	P_1	0.89	2.08	-1.18	0.92	2.21	-1.28	0.94	2.39	-1.45	0.94	2.51	-1.58
		(3.07)	*(1.87)*	*(-1.16)*	*(4.13)*	*(2.64)*	*(-1.65)*	*(5.13)*	*(3.24)*	*(-2.13)*	*(5.99)*	*(3.78)*	*(-2.58)*
	P_3	1.12	1.61	-0.50	1.14	1.70	-0.55	1.20	1.83	-0.63	1.21	1.92	-0.70
		(3.77)	*(3.61)*	*(-1.96)*	*(4.88)*	*(4.45)*	*(-2.57)*	*(5.70)*	*(5.11)*	*(-3.16)*	*(6.38)*	*(5.64)*	*(-3.60)*
12	P_1	0.78	1.92	-1.14	0.80	2.03	-1.22	0.77	3.10	-1.33	0.72	2.15	-1.43
		(2.45)	*(1.77)*	*(-1.14)*	*(3.22)*	*(2.49)*	*(-1.64)*	*(3.95)*	*(2.97)*	*(-2.05)*	*(4.50)*	*(3.39)*	*(-2.44)*
	P_3	0.83	1.02	-0.19	0.86	1.04	-0.18	0.86	1.04	-0.18	0.83	1.02	-0.19
		(3.14)	*(2.55)*	*(-0.83)*	*(3.87)*	*(3.07)*	*(-1.01)*	*(4.31)*	*(3.37)*	*(-1.19)*	*(4.49)*	*(3.52)*	*(-1.38)*

Average monthly returns on volume-based portfolios in percent and their *t*-statistics in parenthesis are presented here. There is a one month lag between the end of portfolio formation period and the beginning of portfolio performance evaluation period. P_1 is the portfolio of loser stocks and P_3 is the portfolio of winner stocks. Similarly, V_1 is the portfolio of low volume stocks and V_3 is the portfolio of high volume stocks. *J* is the portfolio formation period while *K* is the holding period where *J, K* = 3, 6, 9 and 12 months.

Table 4 (continued). Panel B: Returns on volume-based 2-way sorted portfolios (excluding the top and bottom 1% of observations)

J \ K		3			6			9			12		
		V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3
3	P_1	0.49	1.56	-1.06	0.50	1.47	-0.97	0.48	1.46	-0.99	0.47	1.45	-0.98
		(1.87)	*(2.58)*	*(-2.35)*	*(2.33)*	*(3.26)*	*(-2.98)*	*(2.62)*	*(3.90)*	*(-3.65)*	*(2.87)*	*(4.40)*	*(-4.17)*
	P_3	-0.01	4.24	-4.25	-0.05	4.30	-4.35	-0.06	4.36	-4.42	-0.07	4.39	-4.47
		(-0.05)	*(4.32)*	*(-4.60)*	*(-0.31)*	*(6.02)*	*(-6.44)*	*(-0.45)*	*(7.08)*	*(-7.51)*	*(-0.65)*	*(8.08)*	*(-8.50)*
6	P_1	0.03	1.59	-1.55	-0.02	1.49	-1.51	-0.05	1.47	-1.52	-0.08	1.48	-1.56
		(0.12)	*(2.49)*	*(-3.21)*	*(-0.11)*	*(5.29)*	*(-4.34)*	*(-0.29)*	*(3.77)*	*(-5.13)*	*(-0.49)*	*(4.27)*	*(-5.68)*
	P_3	-0.24	3.87	-4.11	-0.34	3.85	-4.19	-0.36	3.91	-4.27	-0.40	3.99	-4.39
		(-1.02)	*(3.88)*	*(-4.38)*	*(-1.84)*	*(5.29)*	*(-6.17)*	*(-2.31)*	*(6.32)*	*(-7.44)*	*(-2.82)*	*(7.20)*	*(-8.50)*
9	P_1	0.26	3.17	-2.91	0.24	3.25	-3.01	0.23	3.39	-3.16	0.23	3.48	-3.25
		(0.92)	*(2.87)*	*(-3.00)*	*(1.07)*	*(4.00)*	*(-4.18)*	*(1.23)*	*(4.67)*	*(-4.91)*	*(1.40)*	*(5.33)*	*(-5.62)*
	P_3	0.17	2.44	-2.27	0.16	2.52	-2.37	0.19	2.67	-2.48	0.19	2.75	-2.55
		(0.80)	*(5.00)*	*(-6.85)*	*(0.93)*	*(6.00)*	*(-8.22)*	*(1.29)*	*(6.86)*	*(-9.21)*	*(1.51)*	*(7.50)*	*(-9.85)*
12	P_1	0.23	3.10	-2.87	0.22	3.27	-3.04	0.21	3.35	-3.14	0.20	3.41	-3.21
		(0.81)	*(2.79)*	*(-2.90)*	*(0.99)*	*(3.87)*	*(-4.04)*	*(1.15)*	*(4.51)*	*(-4.75)*	*(1.29)*	*(5.09)*	*(-5.36)*
	P_3	0.08	1.76	-1.68	0.07	1.76	-1.69	0.06	1.78	-1.72	0.03	1.75	-1.72
		(0.36)	*(3.87)*	*(-5.08)*	*(0.38)*	*(4.59)*	*(-6.21)*	*(0.41)*	*(5.05)*	*(-6.74)*	*(0.23)*	*(5.26)*	*(-6.97)*

Average monthly returns on volume-based portfolios in percent and their *t*-statistics in parenthesis are presented here. There is a one month lag between the end of portfolio formation period and the beginning of portfolio performance evaluation period. P_1 is the portfolio of loser stocks and P_3 is the portfolio of winner stocks. Similarly, V_1 is the portfolio of low volume stocks and V_3 is the portfolio of high volume stocks. *J* is the portfolio formation period while *K* is the holding period where *J, K* = 3, 6, 9 and 12 months. Observations based on extreme share turnover have been excluded in order to account for possible serious impact on the results.

The pattern in average monthly returns becomes clearly visible after excluding the 1% of extreme observations based on share turnover in Panel B of table 4. The returns on high-volume portfolios are all positive and statistically significant while for low-volume portfolios, the returns varies between -0.40% and 0.50% but significant for only the 3 x 6 losers (0.50%), 3 x 9 losers (0.48%), 3 x 12 losers (0.47%) and the 6 x 12 winners (-0.40%) portfolios. The volume discount returns (V_1-V_3) for all portfolio formation and holding periods are negative and highly statistically significant. This indicates that high-volume portfolios do on average outperform low-volume portfolios on the Helsinki Stock Exchange.

4.2 Risk adjustments to volume-based portfolios

In order to determine that the returns patterns documented in table 4 are not driven by firm specific characteristics such as firm size and book-to-market ratio, I adjust the returns for known risk factors in the stock market. I employ the use of Fama and French (1993) three-factor model. This model has been shown to explain the returns in US equities market. International evidences also abound regarding the explanatory power of the three factor model (Fama & French, 2012).

To adjust the returns for common risk factors in stock returns. I aggregate the time series of returns for the different portfolios and run a regression following the model in equation 7.

$$R_{it} - rf_t = \alpha_i + \beta_i(R_{mt} - rf_t) + h_i HML_t + s_i SMB_t + e_{it} \tag{7}$$

$where$

$R_{it} = time\ series\ returns\ of\ portfolio\ i$

$rf_t = one\ month\ Euribor\ rate$

$\alpha_i = abnormal\ returns\ on\ portfolio\ i$

$R_{mt} - rf_t = excess\ returns\ on\ the\ market\ portfolio$

$HML_t = value\ factor$

$SMB_t = size\ factor$

$e_{it} = error\ term\ of\ the\ regression$

$\beta_i, h_i\ and\ s_i\ are\ respectively\ the\ loadings\ on\ the\ market, value\ and\ size\ factors$

Table 5. Panel A – Abnormal returns conditional on the three-factor Fama-French (1993) model, α

J \ K		3			6			9			12		
		V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3
3	P_1	-0.79	-0.46	-2.67	-1.05	-0.79	-2.60	-1.13	-0.98	-2.48	-1.22	-1.16	-2.39
		(-2.04)	*(-0.68)*	*(-5.78)*	*(-3.22)*	*(-1.51)*	*(-8.09)*	*(-3.93)*	*(-2.22)*	*(-9.36)*	*(-4.84)*	*(-2.99)*	*(-9.88)*
	P_3	-0.97	1.62	-4.91	-1.28	1.34	-4.95	-2.44	4.54	-9.27	-1.46	1.00	-4.79
		(-1.61)	*(1.39)*	*(-4.44)*	*(-2.93)*	*(1.63)*	*(-6.41)*	*(-24.06)*	*(20.64)*	*(-40.18)*	*(-4.98)*	*(1.61)*	*(-8.38)*
6	P_1	-1.01	-0.46	-2.88	-1.27	-0.89	-2.72	-1.36	-1.00	-2.70	-1.47	-1.13	-2.67
		(-2.53)	*(-0.69)*	*(-6.33)*	*(-3.88)*	*(-1.72)*	*(-7.95)*	*(-4.73)*	*(-2.23)*	*(-8.74)*	*(-5.82)*	*(-2.84)*	*(-9.02)*
	P_3	-1.35	1.59	-5.28	-1.51	1.23	-5.07	-2.27	-0.80	-3.58	-1.69	0.76	-4.78
		(-3.88)	*(1.32)*	*(-4.73)*	*(-5.50)*	*(1.44)*	*(-6.63)*	*(-18.94)*	*(-2.48)*	*(-13.62)*	*(-7.67)*	*(1.17)*	*(-8.59)*
9	P_1	-0.91	1.40	-4.64	-1.11	1.31	-4.76	-1.14	1.16	-4.64	-1.19	0.97	-4.50
		(-2.53)	*(1.06)*	*(-3.85)*	*(-3.68)*	*(1.33)*	*(-5.22)*	*(-4.31)*	*(1.32)*	*(-5.75)*	*(-5.13)*	*(1.22)*	*(-6.15)*
	P_3	-0.68	0.19	-3.21	-0.84	-0.08	-3.10	-0.99	-0.14	-3.24	-1.03	-0.31	-3.05
		(-1.79)	*(0.36)*	*(-9.89)*	*(-2.71)*	*(-0.17)*	*(-10.96)*	*(-39.74)*	*(-3.64)*	*(-127.7)*	*(-4.09)*	*(-0.77)*	*(-11.03)*
12	P_1	-0.86	0.97	-4.50	-1.08	1.02	-4.37	-1.17	0.89	-4.33	-1.29	0.59	-4.15
		(-2.13)	*(0.73)*	*(-6.15)*	*(-3.19)*	*(1.01)*	*(-4.77)*	*(-4.13)*	*(1.00)*	*(-5.42)*	*(-5.31)*	*(0.74)*	*(-5.75)*
	P_3	-0.85	-0.26	-3.05	-0.99	-0.54	-2.71	-1.07	-0.68	-2.66	-1.16	-0.88	-2.55
		(-2.34)	*(-0.50)*	*(-11.03)*	*(-3.12)*	*(-1.19)*	*(-11.79)*	*(-3.68)*	*(-1.64)*	*(-12.88)*	*(-4.35)*	*(-2.24)*	*(-13.21)*

The table 5 reports the regression results relative to the Fama and French (1993) three-factor model for the average monthly returns reported in panel A of table 4. The sample period spans from 1999 to 2010. The result of the table is based on the MSCI Barra country index for Finland and thus represents proxies for the Finnish Fama & French factors. The three-factor model as defined in equation 7 is $R_{it} - rf_t = \alpha_i + \beta_i(R_{mt} - rf_t) + h_i HML_t + s_i SMB_t + e_{it}$. P_1 is the portfolio of loser stocks and P_3 is the portfolio of winner stocks. Similarly, V_1 is the portfolio of low volume stocks and V_3 is the portfolio of high volume stocks. *J* is the portfolio formation period while *K* is the holding period where *J, K* = 3, 6, 9 and 12 months Panel A of table 5 contains the intercept term for the difference portfolio formation period and holding periods and the associated *t*-statistics are in parenthesis.

Table 5 (continued). Panel B – loadings on the market portfolio, β

J \ K		3			6			9			12		
		V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3
3	P_1	0.27	0.39	-0.01	0.20	0.31	0.00	0.18	0.26	0.03	0.16	0.22	0.05
		(6.24)	*(5.28)*	*(-0.22)*	*(5.60)*	*(5.40)*	*(0.11)*	*(5.61)*	*(5.41)*	*(0.97)*	*(5.79)*	*(5.23)*	*(1.87)*
	P_3	0.21	0.40	-0.08	0.14	0.34	-0.09	0.05	0.42	-0.26	0.08	0.25	-0.06
		(3.18)	*(3.12)*	*(-0.63)*	*(2.85)*	*(3.76)*	*(-1.07)*	*(2.67)*	*(10.09)*	*(-5.98)*	*(2.45)*	*(3.67)*	*(-0.94)*
6	P_1	0.24	0.39	-0.04	0.18	0.31	-0.01	0.16	0.27	0.01	0.15	0.24	0.02
		(5.42)	*(5.37)*	*(-0.84)*	*(5.04)*	*(5.42)*	*(-0.32)*	*(5.16)*	*(5.53)*	*(0.18)*	*(5.40)*	*(5.49)*	*(0.70)*
	P_3	0.19	0.39	-0.09	0.16	0.33	-0.05	0.12	0.22	-0.01	0.13	0.21	0.03
		(5.03)	*(2.99)*	*(-0.75)*	*(5.47)*	*(3.55)*	*(-0.65)*	*(7.58)*	*(5.27)*	*(-0.27)*	*(5.25)*	*(3.02)*	*(0.43)*
9	P_1	0.25	0.51	-0.15	0.19	0.46	-0.15	0.18	0.38	-0.09	0.17	0.33	-0.04
		(6.31)	*(3.58)*	*(-1.16)*	*(5.91)*	*(4.27)*	*(-1.51)*	*(6.23)*	*(3.97)*	*(-1.01)*	*(6.71)*	*(3.78)*	*(-0.54)*
	P_3	0.23	0.31	0.04	0.19	0.23	0.07	0.16	0.20	0.08	0.14	0.15	0.11
		(5.71)	*(5.33)*	*(1.03)*	*(5.74)*	*(4.60)*	*(2.35)*	*(60.30)*	*(46.41)*	*(28.10)*	*(5.21)*	*(3.39)*	*(3.52)*
12	P_1	0.26	0.47	-0.09	0.21	0.43	-0.11	0.19	0.37	-0.07	0.17	0.32	-0.03
		(6.14)	*(3.33)*	*(-0.70)*	*(5.77)*	*(4.11)*	*(-1.15)*	*(6.27)*	*(3.99)*	*(-0.83)*	*(6.81)*	*(3.85)*	*(-0.42)*
	P_3	0.24	0.32	0.03	0.21	0.25	0.07	0.18	0.23	0.07	0.17	0.19	0.09
		(6.26)	*(5.98)*	*(1.08)*	*(6.22)*	*(5.36)*	*(2.86)*	*(6.03)*	*(5.24)*	*(3.42)*	*(6.04)*	*(4.68)*	*(4.67)*

The table 5 reports the regression results relative to the Fama and French (1993) three-factor model for the average monthly returns reported in panel A of table 4. The sample period spans from 1999 to 2010. The result of the table is based on the MSCI Barra country index for Finland and thus represents proxies for the Finnish Fama & French factors. The three-factor model as defined in equation 7 is $R_{it} - rf_t = \alpha_i + \beta_i(R_{mt} - rf_t) + h_i HML_t + s_i SMB_t + e_{it}$. P_1 is the portfolio of loser stocks and P_3 is the portfolio of winner stocks. Similarly, V_1 is the portfolio of low volume stocks and V_3 is the portfolio of high volume stocks. *J* is the portfolio formation period while *K* is the holding period where *J, K* = 3, 6, 9 and 12 months Panel B of table 5 reports the loading on the market factor while the corresponding *t*-statistics are in parenthesis.

Table 5 (continued). Panel C – loadings on the size factor, s

J \ K		3			6			9			12		
		V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3
3	P_1	0.25	0.35	-0.02	0.19	0.28	0.00	0.13	0.22	0.00	0.13	0.20	0.02
		(4.72)	*(3.89)*	*(-0.30)*	*(4.41)*	*(3.94)*	*(0.08)*	*(3.48)*	*(3.74)*	*(0.00)*	*(3.79)*	*(3.80)*	*(0.51)*
	P_3	0.23	0.37	-0.05	0.20	0.34	-0.06	0.07	0.53	-0.40	0.14	0.27	-0.05
		(2.90)	*(2.39)*	*(-0.37)*	*(3.44)*	*(3.12)*	*(-0.55)*	*(5.33)*	*(17.26)*	*(-12.46)*	*(3.47)*	*(3.25)*	*(-0.63)*
6	P_1	0.25	0.39	-0.06	0.20	0.33	-0.05	0.15	0.27	-0.04	0.15	0.26	-0.03
		(4.67)	*(4.44)*	*(-0.97)*	*(4.47)*	*(4.79)*	*(-1.04)*	*(3.93)*	*(4.61)*	*(-0.89)*	*(4.37)*	*(4.92)*	*(-0.69)*
	P_3	0.16	0.38	-0.14	0.14	0.33	-0.10	0.05	0.15	-0.07	0.11	0.27	-0.07
		(3.43)	*(2.39)*	*(-0.93)*	*(3.94)*	*(2.93)*	*(-1.01)*	*(3.43)*	*(3.82)*	*(-2.11)*	*(3.84)*	*(3.08)*	*(-0.89)*
9	P_1	0.24	0.49	-0.16	0.19	0.43	-0.14	0.16	0.34	-0.09	0.16	0.35	-0.10
		(5.10)	*(2.81)*	*(-1.00)*	*(4.78)*	*(3.24)*	*(-1.19)*	*(4.60)*	*(2.89)*	*(-0.83)*	*(5.13)*	*(3.30)*	*(-1.05)*
	P_3	0.17	0.21	0.05	0.16	0.17	0.08	0.15	0.17	0.07	0.13	0.14	0.08
		(3.43)	*(2.99)*	*(1.09)*	*(3.82)*	*(2.69)*	*(2.08)*	*(44.40)*	*(32.46)*	*(19.21)*	*(3.84)*	*(2.59)*	*(2.07)*
12	P_1	0.21	0.52	-0.23	0.16	0.43	-0.20	0.12	0.33	-0.13	0.12	0.36	-0.16
		(3.80)	*(2.83)*	*(-1.37)*	*(3.41)*	*(3.14)*	*(-1.56)*	*(3.06)*	*(2.67)*	*(-1.17)*	*(3.49)*	*(3.26)*	*(-1.64)*
	P_3	0.15	0.20	0.03	0.14	0.15	0.07	0.11	0.13	0.06	0.09	0.12	0.06
		(3.01)	*(2.83)*	*(0.73)*	*(3.14)*	*(2.38)*	*(2.12)*	*(2.68)*	*(2.29)*	*(1.95)*	*(2.55)*	*(2.15)*	*(2.14)*

The table 5 reports the regression results relative to the Fama and French (1993) three-factor model for the average monthly returns reported in panel A of table 4. The sample period spans from 1999 to 2010. The result of the table is based on the MSCI Barra country index for Finland and thus represents proxies for the Finnish Fama & French factors. The three-factor model as defined in equation 7 is $R_{it} - rf_t = \alpha_i + \beta_i(R_{mt} - rf_t) + h_i HML_t + s_i SMB_t + e_{it}$. P_1 is the portfolio of loser stocks and P_3 is the portfolio of winner stocks. Similarly, V_1 is the portfolio of low volume stocks and V_3 is the portfolio of high volume stocks. *J* is the portfolio formation period while *K* is the holding period where *J, K* = 3, 6, 9 and 12 months Panel C of table 5 reports the loading on the size factor while the corresponding *t*-statistics are in parenthesis.

Table 5 (continued). Panel D – loadings on the value factor, h

J \ K		3			6			9			12		
		V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3
3	P_1	-0.01	-0.06	0.04	-0.03	-0.05	0.00	-0.02	-0.06	0.04	-0.03	-0.07	0.03
		(-0.27)	*(-0.69)*	*(0.59)*	*(-0.75)*	*(-0.67)*	*(0.05)*	*(-0.41)*	*(-1.06)*	*(0.99)*	*(-0.81)*	*(-1.25)*	*(0.81)*
	P_3	-0.18	-0.06	-0.13	-0.13	-0.09	-0.05	-0.02	-0.26	0.26	-0.10	-0.10	-0.01
		(-2.18)	*(-0.37)*	*(-0.86)*	*(-2.15)*	*(-0.78)*	*(-0.49)*	*(-1.66)*	*(-9.02)*	*(8.44)*	*(-2.42)*	*(-1.18)*	*(-0.11)*
6	P_1	-0.03	-0.10	0.05	-0.04	-0.09	0.04	-0.04	-0.10	0.05	-0.04	-0.11	0.05
		(-0.63)	*(-1.08)*	*(0.83)*	*(-0.87)*	*(-1.26)*	*(0.81)*	*(-0.99)*	*(-1.60)*	*(1.08)*	*(-1.29)*	*(-2.02)*	*(1.31)*
	P_3	-0.03	-0.07	0.02	-0.02	-0.06	0.02	0.08	0.18	-0.06	-0.04	-0.10	0.05
		(-0.73)	*(-0.39)*	*(0.12)*	*(-0.66)*	*(-0.52)*	*(0.23)*	*(6.87)*	*(5.87)*	*(-2.36)*	*(-1.17)*	*(-1.08)*	*(0.63)*
9	P_1	-0.03	-0.09	0.05	-0.04	-0.07	0.02	-0.05	-0.14	0.08	-0.05	-0.17	0.10
		(-0.52)	*(-0.49)*	*(0.29)*	*(-0.89)*	*(-0.54)*	*(0.17)*	*(-1.27)*	*(-1.16)*	*(0.72)*	*(-1.54)*	*(-1.48)*	*(0.97)*
	P_3	-0.04	-0.04	-0.02	-0.05	-0.05	-0.01	-0.08	-0.12	0.02	-0.07	-0.11	0.02
		(-0.83)	*(-0.57)*	*(-0.35)*	*(-1.03)*	*(-0.69)*	*(-0.37)*	*(-24.16)*	*(-21.73)*	*(5.96)*	*(-2.09)*	*(-1.87)*	*(0.47)*
12	P_1	0.02	-0.08	0.09	0.01	-0.06	0.07	0.01	-0.10	0.10	0.00	-0.14	0.14
		(0.26)	*(-0.41)*	*(0.51)*	*(0.18)*	*(-0.44)*	*(0.52)*	*(0.23)*	*(-0.76)*	*(0.89)*	*(0.03)*	*(-1.20)*	*(1.31)*
	P_3	0.01	-0.04	0.05	-0.01	-0.01	0.00	-0.02	-0.05	0.02	-0.01	-0.04	0.02
		(0.22)	*(-0.56)*	*(1.15)*	*(-0.12)*	*(-0.09)*	*(-0.10)*	*(-0.49)*	*(-0.82)*	*(0.82)*	*(-0.30)*	*(-0.67)*	*(0.80)*

The table 5 reports the regression results relative to the Fama and French (1993) three-factor model for the average monthly returns reported in panel A of table 4. The sample period spans from 1999 to 2010. The result of the table is based on the MSCI Barra country index for Finland and thus represents proxies for the Finnish Fama & French factors. The three-factor model as defined in equation 7 is $R_{it} - rf_t = \alpha_i + \beta_i(R_{mt} - rf_t) + h_i HML_t + s_i SMB_t + e_{it}$. P_1 is the portfolio of loser stocks and P_3 is the portfolio of winner stocks. Similarly, V_1 is the portfolio of low volume stocks and V_3 is the portfolio of high volume stocks. *J* is the portfolio formation period while *K* is the holding period where *J, K* = 3, 6, 9 and 12 months. Panel D of table 5 reports the loading on the value factor while the corresponding t-statistics are in parenthesis.

Table 5 (continued). Panel E – adjusted R^2

K / J		3			6			9			12		
		V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3
3	P_1	0.25	0.19	0.00	0.21	0.19	0.00	0.19	0.19	0.01	0.21	0.18	0.03
	P_3	0.10	0.08	0.02	0.10	0.11	0.01	0.06	0.34	0.22	0.09	0.11	0.01
6	P_1	0.22	0.21	0.01	0.20	0.22	0.01	0.18	0.22	0.01	0.20	0.22	0.02
	P_3	0.17	0.07	0.01	0.20	0.10	0.01	0.16	0.19	0.12	0.19	0.09	0.01
9	P_1	0.27	0.10	0.01	0.24	0.14	0.02	0.25	0.12	0.01	0.28	0.12	0.01
	P_3	0.21	0.18	0.01	0.21	0.15	0.05	0.20	0.14	0.06	0.20	0.11	0.10
12	P_1	0.26	0.11	0.02	0.23	0.15	0.02	0.24	0.13	0.01	0.28	0.13	0.02
	P_3	0.24	0.23	0.04	0.24	0.19	0.08	0.23	0.19	0.11	0.23	0.16	0.16

The table 5 reports the regression results relative to the Fama and French (1993) three-factor model for the average monthly returns reported in panel A of table 4. The sample period spans from 1999 to 2010. The result of the table is based on the MSCI Barra country index for Finland and thus represents proxies for the Finnish Fama & French factors. The three-factor model as defined in equation 7 is $R_{it} - rf_t = \alpha_i + \beta_i(R_{mt} - rf_t) + h_i HML_t + s_i SMB_t + e_{it}$. P_1 is the portfolio of loser stocks and P_3 is the portfolio of winner stocks. Similarly, V_1 is the portfolio of low volume stocks and V_3 is the portfolio of high volume stocks. *J* is the portfolio formation period while *K* is the holding period where *J, K* = 3, 6, 9 and 12 months. The adjusted R^2 is reported in panel E of the table.

The Finnish Fama and French factors are used and are constructed from the MSCI Barra country indices for Finland. There is a concern about the use of these factors. The methodology used by Fama and French in constructing the factors may not be reliable in a small exchange, thus one can expect the three –factor model to do a fairly poor job in explaining the returns in the Helsinki Stock Exchange. The results of the regression model in table 5 are at best approximate values and this is also reflected in the reported R^2.

The result of the risk adjustments is shown in table 5. In Panel A of table 5, the monthly abnormal returns are reported. The result is generally consistent with the observed pattern of average monthly returns obtained in table 4. More worthy of note is that the volume discounts (i.e the cells V_1-V_3) are even larger in the risk adjusted abnormal returns than those observed in table 4. The highest volume discount is -9.27% (*t*-statistics = -40.18) and occurs in the 3 x 9 strategy for winners portfolios. The lowest volume discount occur in the 3 x 12 strategy for losers portfolios at -2.39% (*t*-statistics = -9.88). Also, high volume portfolios for both winners and losers outperform portfolios of low volume stocks. These results are in stark contrast to earlier empirical studies on the volume – return dynamics.

Panels B, C and D of table 5 report the loadings on the market, size and value factors respectively. These loadings are useful in determining if the average monthly returns are a result of exposure to these risk factors. Panel B contains the loadings on the market portfolio. These loadings are all below one and are mostly statistically significant indicating that the return patterns are not due to exposure to the market portfolio. The market beta for high volume portfolios are on average higher than the beta for low-volume portfolios which presumes that high volume portfolios have more exposure to the market portfolio than low volume portfolios. The size factor loading for high volume portfolios reveals an intriguing pattern in the returns of high- and low-volume stocks. The SMB beta for all high volume portfolios is higher than those of low-volume stocks suggesting that high-volume portfolios behave more like small firms while low volumes behave more like large firms. The loading on the HML factor is close to zero and not statistically significant for most portfolios indicating that value effect cannot be adjudged to account for the differences in returns profile of the different volume-based portfolios. Panel E reports the adjusted R^2 of the regression. The values are quite small and therefore, the three factor model does not adequately describe the source of the variation in the cross section of volume-based portfolios on the Helsinki Stock Exchange.

Table 6. Returns on volume-based 2-way sorted portfolios using dollar volume as a measure of trading volume

J \ K		3			6			9			12		
		V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3	V_1	V_3	V_1-V_3
3	P_1	1.15	0.85	0.30	1.13	0.87	0.26	1.11	0.86	0.25	1.09	0.82	0.27
		(3.97)	*(1.61)*	*(0.82)*	*(5.10)*	*(2.13)*	*(0.92)*	*(5.98)*	*(2.52)*	*(1.00)*	*(6.54)*	*(2.68)*	*(1.18)*
	P_3	0.14	3.88	-3.74	0.12	3.93	-3.82	0.11	3.98	-3.87	0.10	4.06	-3.95
		(0.57)	*(3.77)*	*(-3.92)*	*(0.62)*	*(5.27)*	*(-5.50)*	*(0.70)*	*(6.31)*	*(-6.53)*	*(0.75)*	*(7.32)*	*(-7.53)*
6	P_1	0.61	0.61	0.00	0.50	0.63	-0.13	0.48	0.65	-0.17	0.47	0.61	-0.15
		(2.02)	*(1.17)*	*(0.00)*	*(2.20)*	*(1.59)*	*(-0.50)*	*(2.51)*	*(1.96)*	*(-0.75)*	*(2.78)*	*(2.07)*	*(-0.73)*
	P_3	0.08	1.51	-1.43	0.03	1.48	-1.46	0.03	1.52	-1.49	0.00	1.56	-1.56
		(0.35)	*(3.17)*	*(-4.25)*	*(0.15)*	*(4.03)*	*(-5.49)*	*(0.17)*	*(4.84)*	*(-6.41)*	*(0.00)*	*(5.46)*	*(-7.01)*
9	P_1	0.69	0.68	0.01	0.66	0.81	-0.16	0.70	0.88	-0.18	0.73	0.89	-0.16
		(2.23)	*(1.28)*	*(0.05)*	*(2.77)*	*(1.93)*	*(-0.61)*	*(3.45)*	*(2.36)*	*(-0.78)*	*(4.02)*	*(2.56)*	*(-0.74)*
	P_3	0.19	2.34	-2.14	0.19	2.53	-2.34	0.22	2.79	-2.57	0.20	2.98	-2.78
		(0.84)	*(3.66)*	*(-4.12)*	*(1.12)*	*(4.70)*	*(-5.08)*	*(1.43)*	*(5.33)*	*(-5.61)*	*(1.50)*	*(5.79)*	*(-6.03)*
12	P_1	0.70	0.59	0.11	0.66	0.61	0.06	0.64	0.60	0.04	0.61	0.54	0.08
		(2.46)	*(1.14)*	*(0.34)*	*(3.03)*	*(1.56)*	*(0.24)*	*(3.52)*	*(1.82)*	*(0.04)*	*(3.88)*	*(1.86)*	*(0.45)*
	P_3	0.42	0.92	-0.49	0.45	0.86	-0.41	0.47	0.81	-0.34	0.44	0.73	-0.29
		(1.66)	*(2.38)*	*(-2.08)*	*(2.18)*	*(2.76)*	*(-2.20)*	*(2.46)*	*(2.89)*	*(-2.09)*	*(2.48)*	*(2.80)*	*(-1.90)*

This table presents average monthly returns in percent and their corresponding *t*-statistics for volume-based portfolio using dollar trading volume as the volume measure. There is a one month lag between the end of portfolio formation period and the beginning of portfolio performance evaluation period. P_1 is the portfolio of loser stocks and P_3 is the portfolio of winner stocks. Similarly, V_1 is the portfolio of low volume stocks and V_3 is the portfolio of high volume stocks. *J* is the portfolio formation period while *K* is the holding period where *J, K* = 3, 6, 9 and 12 months

4.3 An alternative volume measure

In this section, I use an alternative measure as proxy for trading volume to determine if the patterns observed in table 3 will still hold. The alternative trading volume proxy is the dollar trading volume. This has been extensively used in asset pricing studies.

Brennan *et al.* (1998) have used the dollar volume and find that it is strongly negatively associated with returns for both NYSE and NASDAQ stocks. Also in Chordia *et al.* (2001), dollar trading volume and turnover rate are used as proxies for trading volume. My conjecture is that since turnover rate also employs the use of dollar trading volume in its derivation, there should not be much difference between the results based on these two proxies of trading volume. While trading turnover normalises the trading activities across different firm sizes, I believe share turnover should do a better job. Nonetheless, I expect similar result to hold using dollar trading volume as a measure of trading volume.

Table 6 reports the average monthly returns to volume based portfolios using dollar trading volume as a measure of trading volume. Similar pattern of average monthly returns is observable for tables 4 and 6. For the winner portfolios, high volume stocks outperform low-volume discounts and the returns are statistically significant for all portfolio formation and holding periods except for the 12 x 12 strategy. The return on the volume discounts for winner portfolios is highest for the 3 x 12 strategy at -3.95% (t-statistics = -7.53). The volume discounts for losers portfolio is mixed. For example, while the 9 x 12 strategy for high volume loser portfolios reports an average return of 0.88% (*t*-statistics = 2.36) the corresponding figure for low volume loser portfolios is 0.70% (t-statistics = 3.45) resulting in a volume discount return of -0.18% (*t*-statistics = -0.78). For the 3 x 12 strategy, low volume losers outperform high volume losers by 0.27% but this average monthly return is not statistically significant.

5 CONCLUSION

This thesis examines the profitability of various volume-based portfolio strategies and contributes to the growing number of studies on the volume - return dynamics. This study differs from earlier studies as it focuses on the Helsinki Stock Exchange which represents an emerging stock market. I began the thesis by providing various market efficiency and behavioural biases that have implications for predicting future returns. I also provided evidences based on earlier studies on the profitability of liquidity based trading strategies.

The study uses data from the Helsinki Stock Exchange covering the period from 1999 to 2010 by constructing portfolios based on past return and past trading volume. I started by forming tertile portfolios based on past returns whereby the extreme portfolios were labelled as winner and loser portfolios. I also sort these extreme portfolios into three portfolios based on past trading volume. Based on these sorts, I examined the profitability of various volume based portfolios for different formation and holding periods. Based on earlier theoretical literature and empirical evidences, I conjectured that portfolios of low-volume stocks would outperform high-volume portfolios.

Contrary to prior literature, I find that conditional on past returns high-volume portfolios outperform low-volume portfolio for most formation and holding period although not uniformly significant. The difference in returns between low-volume portfolios and high-volume portfolios appears to be larger for winner portfolios than for loser portfolios. In addition, the results documented in this study are robust to risk adjustments as well as in data excluding extreme observations

The results obtained from this thesis do not entirely provide support for earlier empirical studies. I contend that the small market size and non-synchronous trading in the Helsinki Stock Exchange are plausible reasons for the difference in my findings compared to earlier studies. The paper has several implications for investors interested in the Finnish stock market. A thinly traded stock market such as the Helsinki Stock Exchange may not accommodate large trades for institutional investors without price impact. An understanding of the special characteristics of the Finnish stock market is crucial to implementing a financially sensible and economically profitable volume-based investment strategy.

In spite of the fact that the results from this thesis suggest that investing in portfolios of high-volume stocks and shorting portfolios of stocks with low-volume is a profitable trading strategy, implementing such trading strategy should be undertaken with caution. As explained earlier, there are plausible explanations for the profitable trading strategies documented in this paper. Therefore, the results do not necessarily mean that investors will generate abnormal returns by mechanically implementing these trading strategies.

Further research on the profitability of volume-based portfolios on the Helsinki Stock Exchange may apply different volume measures such as bid-ask spread, dollar volume, and tradable turnover. One can better understand the dynamics of the return – volume relationship on the Helsinki Stock Exchange by applying these alternative volume measures. In addition, by controlling for non-synchronous trading, the power of the results can be further improved.

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