The Predictive Power of Price Gaps

Robert Mois* — *Stockholm School of Economics*

Eric Teder** — *Stockholm School of Economics*

Bachelor Thesis
Stockholm School of Economics
Department of Finance
Tutor: Paolo Sodini
May 30, 2012

Abstract

Price gaps are identified by studying trading ranges, which is the spread between a stock's highest and lowest traded price over a trading day. If the trading ranges of two consecutive days do not overlap, a price gap has occurred. A positive gap is when the lowest traded price of the day is higher than the highest traded price of the precedent day. For negative gaps, the highest traded price of the day is lower than the lowest traded price the day before. Our hypothesis is that abnormal returns can be generated from buying stocks after a positive gap and from short-selling stocks after a negative gap. Using transaction data from the Swedish stock market from 2000 through 2010, we test our hypothesis. First we map returns and abnormal returns, generated from risk-adjusting models, for holding periods of one to five days. The abnormal returns are then the base for executed regressions, run in order to test the explanatory power of positive and negative price gaps. From our analysis, we find support for our hypothesis that trading on positive gaps generates abnormal returns. These abnormal returns persist even after taking transaction costs into account. The same support is not found for negative gaps. According to our findings, price gaps seem to constitute an anomaly.

Keywords: Price gaps, Technical analysis, Momentum, Candlesticks

---

First and foremost, we would like to thank our tutor Paolo Sodini, Associate Professor at the Department of Finance at the Stockholm School of Economics, for generous support and valuable input throughout the work with this thesis. We also especially want to thank Nikita Koptyug for his support and kind assistance. Finally, we are very grateful to Erik Eklund for providing the dataset.

* 21599@student.hhs.se

** 21736@student.hhs.se

CONTENTS

I INTRODUCTION

Action is a disputed source of success in the world of trading. Advocates of the efficient market hypothesis would simply argue that action does not increase profits. The hypothesis of this thesis rests on the words of Pablo Picasso–

"Action is the foundational key to all success".

Our interest for price gaps was raised after having identified the price pattern repeatedly by observing the stock market. It struck us that the phenomenon constituted a certain signal, and that it would be possible to elaborate on trading strategies following this specific signal. Our hypothesis is that it is profitable to trade on price gaps through buying after positive gaps and short-selling after negative gaps, and in this thesis we aim to explore these hypotheses.[1] As it could be argued that the strategy of trading on a price gap is an extension of the momentum strategy of buying winners and selling losers, particular emphasis has been put to distinguish this phenomena from the momentum strategy.

The key to identify inter-day price gaps is the trading range, which is the spread between a stock's highest and lowest price over a trading day. Throughout this study a gap is said to occur when the trading range of a stock does not overlap over two consecutive trading days. Consequently an inter-day gap can occur for two distinct reasons. First, the stock may experience a strong trend when a trading day's lowest traded price is higher than the precedent trading day's highest stock price. This occurrence is defined in the study as a positive gap. Second, a stock may have experienced a fall in its price from the precedent trading day which is not recovered anytime throughout the day. That is, the highest traded price on a certain day is lower than the lowest traded price on the prior trading day. This form of a gap is defined as a negative gap.[2,3] Gaps may occur for a number of reasons, including company announcements, industry specific news or without any specific cause.

It is important to differentiate between the gap size over two days and the stock return over the same two days. We define the gap size as the size of the trading spread between two days, on which a gap has occurred, in relation to the second day's low price (for positive gaps) or high price (for negative gaps). This differs from the one-day return of a stock, which we define as the daily change of a stock's closing price measured in percent. This study investigates the profitability on acting on different gap sizes and their respective explanatory power.

The size of a gap between day *n-1* and *n* is defined as:

$$Positive\ Gap\ Size = \frac{Low_n - High_{n-1}}{Low_n}$$

$$Negative\ Gap\ Size = \frac{Low_{n-1} - High_n}{High_n}$$

The term price gap used throughout this study is in line with that of traditional technical analysis, while the term used in candlestick analysis, a subgroup within technical analysis, is window.

In line with early literature on technical analysis and candlesticks testing profitability of strategies, we take transaction costs into consideration (Griffioen 2003). This measure is also motivated since previously thought

[1] For an illustration of the hypothesis of price continuation after a positive price gap see Figure A1 in Appendix A.
[2] For an illustration of the price gaps pattern see Figure A2 in Appendix A.
[3] For a visual explanation of the components of candlesticks see Figure A3 in Appendix A.

profitable strategies were proven useless after accounting for transaction costs (Fama and Blume 1966). Furthermore, we want to test the price gap model as if we would use the strategy in a real world, thus presenting a more accurate level of profitability.

We acknowledge how our proposed strategy may constitute an example of a short-term momentum strategy as our hypothesis is that profits can be made from buying stocks experiencing a strong one-day positive return and selling stocks experiencing a strong one-day downturn. To prove our strategy distinguishable from the momentum strategy, we have included a momentum factor in our analysis.

By definition, a price gap can only be identified after its occurrence. If a gap occurs between day *n-1* and day *n* the signal is visible at the end of trading at day *n*. In our study we follow the assumption of Brock et al. (1992) that it is possible to trade at the closing price of day *n* and still be able to capture the effect of the gap. This contradicts the requirement of having to identify a gap after its occurrence. Critique has been put forward by Marshall (2008) arguing that a technical analyst would first need to feed estimates of the close price into his/her trading system to see if a signal is generated and then submit a "market at close" order.[4] It is thereafter not sure that the actual close price would be sufficiently similar to the estimated close price that generated the signal, hence acting on an invalid signal. We defend our assumption and contradict Marshall's arguments partly with the use of today's modern trading technology, widely used in the financial industry in high-frequency trading. This would allow us to buy at closing price, or sufficiently close to closing price.[5] A proper algorithm used can also withdraw orders at the closing call if the price is such that the gap vanishes.

Our findings are that abnormal returns following both positive and negative gaps are remarkably high, and also the corresponding risk as measured by the standard deviations. Our findings indicate that trading on positive gaps may be profitable, and from our regressions we find that positive gaps carry significance in explaining post-gap abnormal returns. These results may be explained by theories within behavioral finance. We fail to prove our hypothesis on negative gaps in the general case, but for the sub-section of small sized gaps we find that they do have explanatory power on abnormal returns.

In Section II in this study we present previous literature relevant for the analysis. A description of our data sample is provided in Section III and Section IV presents our approach. In Section V our findings are presented and conclusions from these findings, together with suggestions for future research, are provided in Section VI and VII.

[4] A market-at-close order can be entered anytime during the day and will be executed as near the end of the trading day as possible.
[5] At the Nasdaq Stockholm Stock Exchange continuous trading is halted at 17:25 followed by a pre-close period with no auto matching that lasts until 17:30. In this period orders are collected until the final close where the price is determined by supply and demand (Nasdaq OMX Market Model 2011).

II PREVIOUS LITERATURE

With the hypothesis that the analysis of historic prices may yield profitable trading strategies, this study challenges the theories of market efficiency. This section will provide an overview of previous research on efficient markets together with research conducted that challenges the same. Also theories on technical analysis, which this study constitutes an example of, will be brought up as well as theories within behavioral finance in trying to explain these fields.

EFFICIENT MARKETS

The idea that past prices cannot foresee future prices, the Random Walk Model, was pioneered by Regnault (1863) and Bachelier (1900). The model describes how asset prices follow a random and unpredictable path. Working (1934), Kendall (1953) and Roberts (1959) further stated that price changes, besides following a random walk, are linearly independent. The model gained renewed attention when Malkiel (1973) wrote the famous book "A Random Walk Down Wall Street".

Closely linked to the Random Walk Model is the Efficient Market Hypothesis, drafted by Working (1949) who stated that if it is possible to predict future price movements it has to be due to faulty market expectations. In an efficient market these expectations would have been taken into account. The famous research by Fama (1970) further developed the hypothesis and states that a market is efficient if all available information is impounded in current prices. Almost a decade later than Fama, Jensen (1978) redefined the Efficient Market Hypothesis:

"A market is efficient with respect to information set θ_t if it is impossible to make economic profits by trading on the basis of information set θ_t."[6]

Jensen formed three testable levels of the Efficient Market Hypothesis:

(1) The Weak Form of the Efficient Market Hypothesis, in which the information set θ_t represents all information contained in historical market transaction data, e.g. past prices and trading volume, as of time *t*.
(2) The Semi-Strong Form of the Efficient Market Hypothesis, in which θ_t represents historical market data together with all information that is publicly available at time *t*.
(3) The Strong Form of the Efficient Market Hypothesis, in which θ_t represents all public and private information at time *t,* including insider information.

Another efficient market model explaining the behavior of prices is the Martingale model stating that an asset's expected return is zero when conditioned on the asset's price history (Samuelson 1965 and Mandelbrot 1966). Fama (1970) reviewed the empirical literature on efficient markets and found that there is extensive support for the Efficient Market Hypothesis. He created the Sub-Martingale model suggesting that no trading rules based on historic prices can have higher expected returns than a buy-and-hold strategy in a future period. Comparing the Random Walk Model with the Martingale Model, the former does not only provide a more detailed description of the economic environment but also relies on stronger assumptions. However, Fama and Blue (1966) concluded that the two models are very similar, and for practical purposes identical.

[6] With economic profits Jensen meant risk-adjusted profits net of all transaction costs.

ANOMALIES

A distortion of the Efficient Markets Hypothesis is said to be an anomaly. For this study, the two most relevant anomalies found are the momentum effect and the contrarian effect. The momentum effect is the tendency for rising (falling) asset prices to rise (fall) further. Jegadeesh and Titman (1993) showed that buying past winners and selling past losers created substantial returns. This anomaly, inconsistent with market efficiency theories, has been debated since Jegadeesh and Titman first published their findings and is still extensively used in practice by professional investors.[7] The momentum effect is said to be the only anomaly that is persistent and has survived since its publication (Schwert 2003). Since Jegadeesh and Titman's findings many studies have examined the risk-adjusted returns, using different asset pricing models such as CAPM and Fama-French three-factor model, finding significantly positive alphas and thus concluding that the abnormal returns of the momentum strategy cannot be explained.[8,9] Rouwenhorst (1998) showed how momentum returns were economically large in several European markets, and recent papers find that the momentum strategy yields positive returns in most large markets (Griffin et al. 2003 and Chui et al. 2010).

The academic world still questions why the momentum anomaly has not been arbitraged away, even in the light of the Adaptive Market Hypothesis (Lo 2004), stating that markets have become gradually more efficient due to more technologically sophisticated markets and increased knowledge of how to exploit, and thereby wipe out, market anomalies (e.g. Li et al. 2008). Ali and Trombley (2006) and Agyei-Ampomah (2007) points out short-selling constraints as one explanation for the immortality of the momentum effect, since the profitability of the strategy originates from short selling the loser portfolio.

Numerous explanations for the momentum premium have been presented during the last 30 years. Conrad and Kaul (1998) say the premium is a compensation for risk, Black (1993) and MacKinlay (1995) call it a result of data mining and Korajczyk and Sadka (2004) conclude that the returns are due to an underestimation of transaction costs. Some authors claim that the abnormal returns are illusionary and insignificant (Lesmond et al. 2004; Hanna and Ready 2005). Jegadeesh and Titman (2011) summarize the behavioral interpretation of momentum profits saying that a delayed reaction to firm-specific information is the source. They concluded that investors tend to underreact to firm-specific information. One alternative interpretation is that the delayed reaction is an overreaction by investors who react with delay or who like to chase winners (Daniel et al. 1998).

An opposing theory to the momentum effect is the contrarian effect, brought forward by De Bondt and Thaler (1985; 1987) who were the pioneers in finding long-term overreaction in stock returns. They found that past losers over three to five year periods outperformed past winners over the next three to five years. Jegadeesh (1990) and Lehmann (1990) also found the contrarian strategy to be profitable for short term periods (one week to one month). Furthermore, Lakonishok et al. (1994) and Schiereck et al. (1999) showed that a long term contrarian strategy earned excess returns. Recent studies find that the contrarian strategy still generates abnormal returns (e.g. Wang et al. 2009).

---

[7] See for example Grinblatt et al. (1995) who found that 77 percent of the mutual funds in their sample were momentum investors. Other articles showing the extensive use of the momentum strategy are Badrinath and Wahal (2002) and Mulvey and Kim (2008).

[8] CAPM was developed by Sharpe (1964) and Lintner (1965) and shows the relationship between the risk of an asset and its expected return. Even though the model is based on unrealistic assumptions it has been a popular way to answer the question if profits from anomalies are simply a reward of bearing risky assets.

[9] Jegadeesh and Titman (1993) use CAPM as the risk-adjusting model while Fama and French (1996), Jegadeesh and Titman (2001) and Grundy and Martin (2001) use the Fame-French three-factor model.

TECHNICAL ANALYSIS

Technical analysis is the study of past price movements with the goal of predicting future price movements (Griffioen 2003). If technical analysis is found to be profitable it is a contradiction of the Efficient Market Hypothesis. One of the earliest pioneers within the field was Hamilton (1922) who laid the foundation of the Dow Theory, based on editorials by Charles H. Dow, which later was popularized by Rhea (1932).[10] However, Cowles (1933) found that Hamilton could not beat a continuous investment strategy in the DJIA after looking at the forecasting records. Cowles concluded that a buy-and-hold strategy generated 15.5% annualized returns from 1902-1929 while the Dow Theory strategy produced annualized returns of 12%. Alexander (1964) and Fama and Blume (1966) showed that technical analysis profitability vanishes after taking transaction costs into consideration. With the popularization of the Efficient Markets Theory (Fama 1970), the interest in technical analysis dampened. Based on the fact that previous empirical studies are difficult to compare, because of differences in statistical tests, technical trading rules, markets, time periods and provision for transaction costs, researchers are still skeptical about the usefulness of technical analysis (Malkiel 2011). After articles published by Sweeney (1986) and Brock et al. (1992), showing significant technical trading profits, the empirical research increased substantially.[11] Lo et al. (2000) found evidence in support of technical indicators using automatic pattern recognition with kernel regressions whereas Sullivan et al. (1999) found that the profitability of technical analysis had declined or even vanished in the stock market. Park and Irwin (2004) reviewed 95 empirical studies on technical analysis and summarized that 56 studies presented positive results, 20 studies presented negative results and 19 studies presented mixed results.

One of the oldest technical analysis methods is the candlestick method, dating back to at least the eighteenth century in Japan where the technique was applied to the trading of forward contracts on rice (Lu et al. 2012).[12] The technique was introduced in the West as late as in the 1970s (Nison 1991) and has since grown in popularity (Okamoto 2003). Whereas traditional technical analysis have focused on the daily closing price of an asset when analyzing transaction information, the candlestick method also includes high, low and opening prices. The difference between the opening and closing price is the candlestick's "body".[13] A higher closing price than the opening price (positive return) is illustrated with a white body. A lower closing price than the opening price (negative return) is illustrated with a black body. The lines above and below the body, named "Shadows", illustrate the highest and lowest traded price during the day, respectively.[14]

The candlestick method can also be used for intraday analysis. Fock et al. (2005) evaluated the profitability of candlestick analysis on intraday data but did not find that returns were significantly better than the returns of a benchmark with randomized transactions.[15,16] Horton (2009), Marshall et al. (2006; 2008) used daily data and found little value in the use of candlesticks. Caginalp and Laurent (1998), Goo et al. (2007) and Shiu and Lu (2011) however, found statistically significant evidence of profitability in candlestick patterns. Fiess and MacDonald (2002)

---

[10] Charles. H. Dow (1851-1902) was a journalist, founder and first editor of the Wall Street Journal and co-founder of Dow Jones and Company. The Dow Theory is a form of technical analysis stating that when the Dow Jones Industrial Average and the Dow Jones Transportation Average both hit a new high or a new low for a period of time, it can confirm a previous, bullish or bearish, signal.

[11] Brock et al. (1992) found support in using two of the simplest and most used trading rules, the moving average and the trading range break (support and resistance levels). A support (resistance) level is a price level where the price tends to find support (resistance) as it is falling (rising). Technical analysts claim that the price is more likely to "bounce" off a support level or resistance level rather than break through it.

[12] The derivatives exchange in Japan, the Yodoya rice market in Osaka, was one of the first derivatives exchanges in the world.

[13] For an illustration of the candlestick's components see Figure A3 in Appendix A.

[14] The candlestick methodology and different candlestick patterns have been covered extensively by Nison (1991;1994), Wagner and Matheny (1993), Morris (1995), Bigalow (2002), Pring (2002) and Fischer and Fischer (2003).

[15] They also combined the candlestick patterns with traditional technical analysis patterns, such as the relative strength index, the momentum indicator and moving averages and concluded that the forecasting power of candlestick patterns increased when combining the methods.

[16] When using the candlestick method intraday every candlestick is representing e.g. one minute or one hour depending on the time frame chosen.

argued that a technical analysis of high, low and close prices can generate superior forecasts of volatility and future levels of exchange rates.[17]

Technical analysts extensively use strategies based on the momentum anomaly, such as the Relative Strength Index and Momentum Indicator (Menkhoff and Taylor 2007).[18]

BEHAVIORAL FINANCE

Finding it difficult to explain the profits from momentum and technical analysis strategies with risk-based models, researchers have turned to behavioral models (Jegadeesh and Titman 2011). De Bondt and Thaler (1985; 1987) pioneered the research field of behavioral finance by discovering that people systematically overreact to unexpected news. In contrast to their finding, Zhang (2006) concluded that stock price continuation is due to underreaction to public information by investors and that the effect is strengthened as the information uncertainty, approximated by asset volatility, increases. Hong and Stein (1999) concluded that markets consist of two types of investors, "news watchers" and "momentum traders", resulting in an underreaction for short horizons and an overreaction for longer horizons. Barberis and Shleifer (2003) confirmed this phenomenon. Hong and Stein also formed the Gradual Information Diffusion Model showing that investors obtain information gradually, hence contributing to an underreaction effect. Daniel et al. (1998) found that the behavior of informed traders can be described by a self-attribution bias, saying that investors attributes positive outcomes to their skills and negative outcomes to bad luck. This behavior leads to overconfidence about investors' stock picking ability and consequently their tendency to push up stock prices above fundamental value, creating a delayed overreaction. Price continuation and trend-chasing can be explained by positive feedback rules (De Long et al. 1990) describing the behavior when investors buy when prices rise and sell when prices fall. Some researchers have attributed the price continuations to the theory of self-fulfillment of technical analysis strategies. One example is the finding that the use of trading systems, that tries to exploit price trends in asset market, strengthen and lengthen these trends (Schulmeister 2006; 2007). Also herding behavior[19], of short-horizon traders can lead to informational inefficiency (Banerjee 1992). Froot et al. (1992) stated:

"…the very fact that a large number of traders use chartist models may be enough to generate positive profits for those traders who already know how to chart. Even stronger, when such methods are popular, it is optimal for speculators to choose to chart."

Kahneman and Tversky (1974) in the field of cognitive psychology, showed that individuals tend to rely too heavily on small samples (overestimating their representativeness of the underlying population) and rely too little on large samples (updating prior information too conservatively), a heuristic they named representativeness.[20] The implication of this is that individuals make judgments based on things that they perceive are representative of the problem. Investors would for example anticipate continued strong performance after a series of encouraging earnings announcements.

The Conservatism Bias, also known as the Status-Quo Bias, suggests that individuals tend to undervalue new information when updating past information, thus slowly updating their beliefs when new information arrives (Edward 1968). Barberis et al. (1998) argues that if investors behave according to this bias, prices will slowly adjust

[17] In an attempt to strengthen the returns from using candlesticks, stop-loss strategies were implemented.
[18] The relative strength trading rule has been tested by Jensen (1970) concluding that the profits are not significantly bigger than that from using a buy-and-hold strategy.
[19] Herding behavior describes how individuals tend to imitate the actions of a larger group. However, individually they would not make the same decision. One reason of the existence of herding behavior is social pressure of conformity.
[20] A heuristic can be explained as a rule of thumb individuals follow in when facing different situations.

to new information and lead to underreaction. Essentially investors tend to overvalue new information relative to old (representativeness) and sometimes undervalue new information (conservativeness). Although the Conservatism Bias may in isolation lead to underreaction, this tendency together with the representativeness heuristic can lead to overreaction of prices (Barberis et al. 1998).

Shefrin and Statman (1985), Odean (1998) and Grinblatt and Han (2005) finds that loss-averse investors tend to keep losing positions and sell winning positions, a phenomena called the disposition effect.

Beja and Goldman (1980) developed a disequilibrium model explaining the behavior of prices in the short horizon. They concluded that:

"When price movements are forced by supply and demand imbalances, which may take time to clear, a nonstationary economy must experience at least some transient moments of disequilibrium".

The theory thus provides a behavioral explanation why a technical analysis strategy, exploiting the imbalances, could be profitable.

III DATA

The principal basis for our analysis rests on a dataset, adjusted for the aim of this study. The first part of this section is dedicated to explain our original dataset, and the second part will go into detail on what modifications have been made to this dataset.

DESCRIPTION OF DATA

This study contains panel data for stocks listed on Nasdaq OMX Stockholm (from now on called OMXS) over the time period of January 1, 2000 through December 31, 2010. In addition to data on currently listed stocks, formerly listed stocks on the exchange have been included in order to account for the survivorship bias.[21,22] The dataset has been provided by the Department of Finance at the Stockholm School of Economics and includes daily stock data on intraday high price, low price and close price. The stock data is adjusted for corporate actions. In order to arrive at a dataset suitable for our analysis we have also included data on dividend dates, daily stock turnover measured as total number of shares traded and daily turnover measured in SEK.

The use of a time period of 11 years is due to availability of data from the source used, together with the belief that this time-frame provides a satisfying number of observations in order to be able to make well-founded conclusions from our analysis. The period of 11 years incorporates boom years, consolidating (neutral market) years and recessions, thus providing a good basis to test the profitability of the strategy regardless of the market environment. The decision to only include stocks traded on OMXS was due to our aim of avoiding the illiquidity problem, and OMXS is considered the most liquid exchange in Sweden.[23] The argument to solely look at Sweden and not all Nordic countries is the variation in characteristics among the exchanges, e.g. with regards to transaction costs, liquidity and exchange rules.

Other required input variables in our models include the risk-free rate and the market portfolio, and these two variables have been estimated in accordance with industry standards. As a proxy for the risk-free rate we have used the 30-day Swedish Treasury bill provided by the Riksbank (the National Bank of Sweden). The market portfolio has been estimated with the OMX Stockholm All-Share Index (OMX Stockholm PI) which includes all the shares listed on the OMXS and is value weighted based on market capitalization. The rational to use this certain index is that it is supposed to show current status as well as changes in the market. Other variables included in the dataset are isincodes, number of shares outstanding and market capitalization.

MODIFICATIONS TO THE DATASET

From our original dataset modifications have been made with the intention of obtaining a dataset more suitable for the aim of this study.[24] A set of criteria have to be met in order for an observation to be included in the analysis. First and foremost, as previously mentioned, the stock must have been listed on the OMXS at the time of the observation of the panel data. Our original dataset includes observations on all current (active) OMXS listed stocks

[21] A complete list of included stocks in the dataset can be found in Appendix E.
[22] The survivorship bias is the tendency that failed companies excluded from a sample results in skewed results, since only successful enough companies that manage to survive the full time period are included.
[23] There are numerous reasons to why it is appropriate to remove illiquid stocks from the sample when evaluating the trading strategy. First, trading in illiquid stocks is hard due to lack of share supply (inexistence of order book depth) and a consequence of this is the risk for price manipulation. Second, it can be hard to both enter and exit the position at the time indicated by a model. Third, short-selling in illiquid stocks can be difficult and costly due to shortage of lending supply.
[24] Several empirical studies testing the profitability of technical trading strategies and technical analysis practitioners argue that it is important that the data are from instruments of adequate liquidity to enable investors to earn meaningful amounts of money (Marshall et al. 2007).

as of December 31, 2010 back to each stock's initial public offering or back to January 1, 2000. As a significant share of the companies in our original sample had their IPO on an exchange other than OMXS (e.g. OMX First North, NGM and Aktietorget), this has been corrected for by manually stripping the dataset of company data dating before a company's transfer to OMXS. In the same manner, observations from dead companies[25] included in the sample have been adjusted. The transfer dates used to drop observations have been obtained from the Swedish Tax Agency.

In instances where there has been trading activity on the index (OMXSPI) but no data is available for a stock, a gap has been considered false and has consequently been omitted from the sample. E.g. if a stock has data for Monday and Wednesday but not for Tuesday, whereas OMXSPI does have data for all three days, a gap occurring between Monday and Wednesday has not been taken into account. Hence, for a gap to be included in the sample it must occur between two days on which trading has occurred on the OMXS.

Besides the measure of only including stocks from OMXS, additional adjustments have been taken in order to strip our dataset from illiquid observations. Observations have been deemed illiquid and exempted from the analysis if they do not meet the following three criteria:

(i) A minimum total weekly turnover constraint of one million SEK.
(ii) A minimum daily turnover, in terms of volume, of one hundred shares.
(iii) A minimum stock price of 1 SEK.

To obtain true results, outliers have also been exempt from the study. The worst performing 0.1% on a monthly basis has been excluded, as well as stocks having experienced returns of over 200% per month. Furthermore, companies presenting less than two years of data on the exchange have also been exempted. This modification has been made on the grounds that a minimum of two years of data is required in order to accurately make analysis and to compute stock co-movement with the market portfolio. Finally, we have identified inaccurate observations which have been treated as missing values. Whereas we believe to have found and corrected for the inaccurate observations likely to carry the highest level of impact on our analysis, we acknowledge the possibility of unnoticed inaccuracies still being present in the data. In the process of classifying observations as being inaccurate, recurrent discussions with data experts at Nasdaq OMX Stockholm have been held for further confirmation.

[25] Dead companies is a term for companies formerly listed on an exchange but that have been delisted. Reasons can be either voluntary or involuntary, including violating regulations or failure to meet a listing's requirements.

IV METHODOLOGY

This section will provide an understanding of how this study is conducted. The first step of this study will be to find stock returns following gaps for holding periods of one to five days. The next step will be to find the risk-adjusted and abnormal returns, and the final step of our study will be to run regressions to find the explanatory power of gaps. According to our hypothesis, the risk-adjusted returns will be positive after positive gaps and negative after negative gaps.

FINDING AND RISK-ADJUSTING POST-GAP RETURNS

Returns of our strategy will be calculated as the percentage change in stock *i*'s close price from trading day *t,* on which a gap has occurred, to trading day *t+K*, where *K* ranges from 1 to 5. After having found the returns following gaps, these returns will be adjusted for risk using two models. The reason for analyzing holding periods ranging from 1 to 5 days is because our hypothesis anticipates a short-term momentum effect, and because candlestick analysis has shown to be most valuable with maximum holding periods of under ten days (Morris 1995) which is also the holding periods evaluated in previous empirical research on candlestick patterns (Marshall et al. 2008; Lu et al. 2012). Through the measure of using two risk-adjusting models, we aim to find how much of the return that is not simply attributable to increased risk-taking. The approach will be to first calculate expected return at date *t,* and then observe how much the actual and expected return differs. This difference is the abnormal return at date *t,* called Jensen's alpha, and is a common measure of the portion of a return of a security that is not explained by a risk-adjusting model. Jensen's alpha is given as the residual, or error term, for each observation after a regression. If Jensen's alpha is positive the company has performed better that period, e.g. a day, than predicted by the model and vice versa if the alpha is negative.

The first risk-adjusting model that will be used is the CAPM, which estimates return for an asset through its exposure to the market. The second model will be an extended version of the CAPM, with a momentum factor included. The momentum factor will be a stock's exposure to the momentum portfolio, which will be calculated according Jegadeesh and Titman (1993) who found the profitability of buying past winners and selling past losers, the momentum effect. First, all stocks are ranked at the beginning of each month based on their six-month return after which the portfolio is rebalanced. The portfolio is thus repositioned once a month. The momentum portfolio will then be composed of a long position in the best performing tenth of companies over the last six months, together with a short position in the worst performing tenth of companies over the same time-period. Also the portfolio is equally weighted, further in accordance to Jegadeesh and Titman (1993), as opposed to value weighted. They showed how the difference between the two alternative approaches was very small. In contrast to Jegadeesh and Titman we will evaluate the portfolio on a daily basis as opposed to study holding periods of several months, in order to better fit the aim of our study.

The two models, the CAPM (Model 1) and an extension of the CAPM that includes a computed momentum factor (Model 2), are specified as follows:

The CAPM model, Model 1 to calculate estimated returns of company *i*, $E(r_i)$:

$$E(r_i) = r_f + \beta_{i,mrkt} * (r_{mrkt} - r_f) + \varepsilon_i \quad (1)$$

The extended CAPM model with an included momentum factor, Model 2:

$$E(r_i) = r_f + \beta_{i,mrkt} * \left(r_{mrkt} - r_f\right) + \beta_{i,mom} * r_{mom} + \varepsilon_i \quad (2)$$

Where:

(i) Beta measures company *i*'s exposure to the market, *mrkt*, i.e. $\beta_{i,mrkt} = \frac{Cov(r_i, r_{mrkt})}{Var(r_{mrkt})}$.

(ii) The daily return of the market is termed r_{mrkt}, and is estimated with the OMXSPI.

(iii) The risk-free rate is denoted r_f, and is estimated with the 30-day Swedish T-bill.

(iv) The momentum factor, $\beta_{i,mom}$, expresses exposure to the constructed momentum portfolio.

(v) The error term is ε_i.

The sets of betas are computed daily with rolling regressions using an estimation window of two years, one year forward looking and one year backward looking, for each date.

The abnormal returns from these two models will lay the foundation for the rest of the study, and will be analyzed both directly and in regressions, acting as the dependent variable when examining the explanatory power of price gaps. The abnormal returns are calculated by subtracting the expected return for stock *i* over time *t* to time *t+K*, where *K* takes on values of 1 to 5 and represent the different holding periods analyzed in the study, from the actual returns. Abnormal returns for company *i* are hence obtained as:

$$AR_i = r_i - E(r_i)$$

Resulting in calculations for the two separate models as:

$$AR_i = (r_i - r_f) - \beta_{i,mrkt} * (r_{mrkt} - r_f) \qquad \text{(Model 1)}$$

$$AR_i = (r_i - r_f) - [\beta_{i,mrkt} * (r_{mrkt} - r_f) + \beta_{i,mom} * r_{mom}] \qquad \text{(Model 2)}$$

When studying the returns of a stock following a price gap, sub-groups of observations will be formed. Stocks will be grouped into sub-groups based on company size measured by company market capitalization. These are updated on a yearly basis, thus these groups will be rebalanced once a year. There will be five equally weighted sub-groups for company size. The second ground for group formation is the size of the gaps. The gaps are sorted as follows:

(i) Small-size gaps - gaps of sizes less than 0.5%.

(ii) Mid-size gaps - gaps of sizes as from 0.5% up to 2%.

(iii) Large-size gaps - gaps of sizes above 2%.

Model Specification

An event study model on the panel data, including binary explanatory variables called "dummy variables" will be used to examine the explanatory power of the price gaps. Regressions will be run with the abnormal returns as the dependent variable, and with different sets of dummy variables as the independent variables. Three regression models will be run with the model specifications:

$$AR_i = \beta_{i,0} + \beta_{i,1} * Event_i + \varepsilon_i \qquad \text{(Regression model I)}$$

$$AR_i = \beta_{i,0} + \gamma_i * Event_i * GapSize_{i,j} + \varepsilon_i \qquad \text{(Regression model II)}$$

$$AR_i = \beta_{i,0} + \gamma_{i,1} * Event_i * GapSize_{i,j} + \gamma_{i,2} * Event_i * CompanySize_{i,k} + \varepsilon_i \qquad \text{(Regression model III)}$$

Where:

(i) AR is the abnormal return generated from one of the two specified models for risk-adjusting returns mentioned above, the CAPM model or the Momentum-Extended model.

(ii) Event is the occurrence of either a positive or negative gap, taking on the value 1 if a positive gap has occurred in the regressions for positive gaps, or 1 for a negative gap in the regressions using negative gaps.

(iii) GapSize is a dummy variable taking on the value 1 if the gap belongs to gap size category *j*. Where *j* is either small-size gap, mid-size gap or large-size gap. Used in the regression is a set of interaction terms, designated γ_i in regression II and $\gamma_{i,1}$ in regression III, for Event and GapSize.

(iv) CompanySize is a dummy variable taking on the value 1 if the stock belongs to company size quintile *k*, where *k* ranges from 1 to 5. In order to explain the impact of company size on gap abnormal returns, rather than on abnormal returns in general, gap sizes are included as a set of interaction terms, designated $\gamma_{i,2}$, together with Event which is either a positive or a negative gap depending on regression.

(v) The error term is ε_i.

The results obtained from using this methodology will be presented and conclusions will be made.

V RESULTS

Our findings for positive gaps are in line with our hypothesis that stock prices should continue to rise after a positive gap. For negative gaps, we fail to show that a similar effect exists but it rather seems that abnormal returns following a negative gap vary. We find the highest return for our strategy to appear from daily trading, i.e. to have a holding period of one day, and from trading at the largest gaps. However, as transactions costs are taken into consideration, the monthly calculated return is lowered. In general, the volatility of returns as measured by standard deviation is very high.

DESCRIPTIVE STATISTICS

An important review after having identified gaps is to screen where these gaps occur. This information will enable us to further understand the nature of gaps, which in turn is critical when drawing conclusions from the analysis.

We find a total of 70,118 gaps in our sample[26], resulting in a frequency of gaps per month and firm of around 2.15.[27] On average the gap size, according to our stated definition, is around 1.7%. There seems to be no major difference between the number of positive and negative gaps, as there are 35,600 positive gaps compared to 34,518 negative gaps making a total of 70,118 gaps, 10.8% of total observations (649,221). Only looking at liquid observations, the correspondent figure is 7.7%.

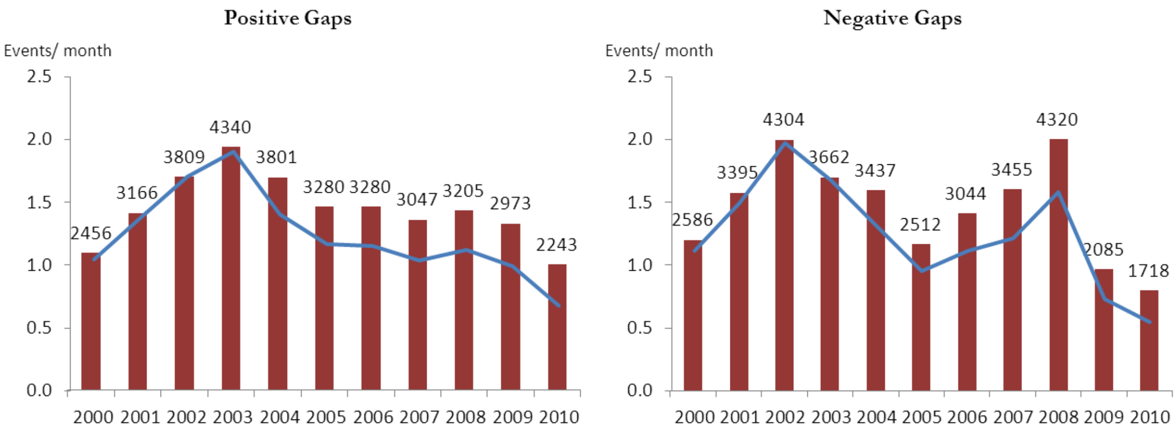
Differences can be seen when comparing companies of different market capitalizations. As can be viewed in Table B1 in Appendix B small companies tend to have a considerably larger frequency of gaps, both positive and negative. This frequency seems to steadily decline with an increase in market capitalization. Furthermore, the gap sizes tend to be larger on average for smaller companies, and the variance of gap size seems to be larger as well. When comparing the smallest quintile of companies with the largest quintile it can be shown that the frequency of gaps in the smallest size group exceeds that in the largest group almost with a factor three. As smaller companies in general are associated with a higher level of volatility in prices, these results are in line with expectations.

[26] Details are described in Table B1 in Appendix B. Mentioned number refers to all gaps, both considered liquid and illiquid. Table B1 further describes prevalence of gaps in these two sub-groups.

[27] Meaning that on average for all stocks in the sample, a gap will occur twice every month. Throughout this study, a month is considered as having 20 days of trading, and calculations are based on this assumption.

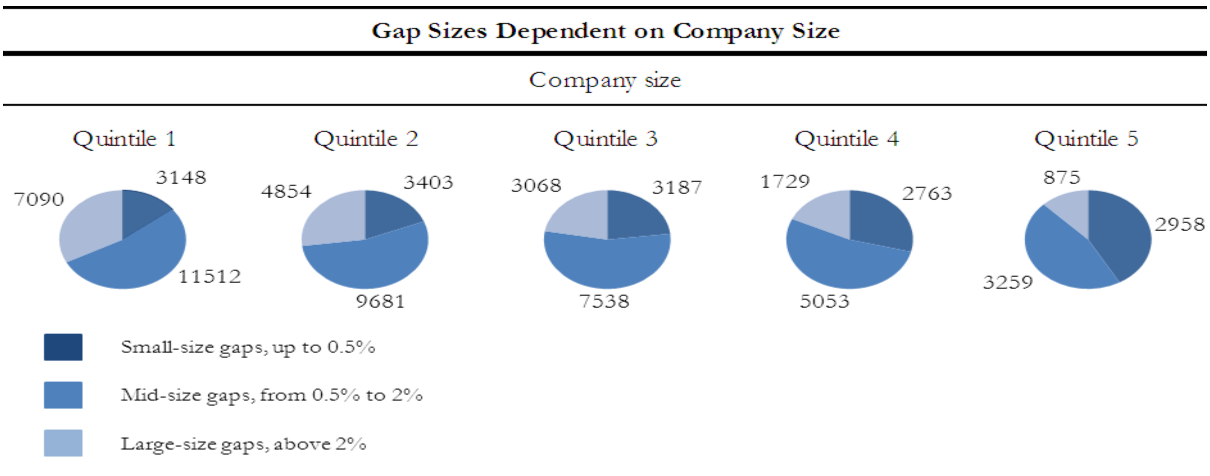
When looking at the number of gaps per year, the year of 2000 and that of 2010 stands out as having fewer events and year 2002 and 2003 as having above average number of gaps, see illustration below.

Figure 1: Distribution and Frequency of Gaps, For Years 2000-2010, Unadjusted for Illiquid Observations



The columns represent observed gaps per year and the line displays average frequency of gaps per month per company for each year. A clear rise in number of negative price gaps is seen during 2008, when the financial turmoil reached its peak, the same rise was not seen for positive gaps. During times of financial instability market volatility tends to go up which could explain this as an increase in volatility is likely associated with an increase in the frequency of gaps, especially for illiquid stocks. During our sample period, two distinct peaks appear, most noticably when looking at negative gaps. Another peak is in the region of the years of 2001/2002, in the aftermath of the bursted dot-com bubble.[28] What is remarkable is the sharp fall in the frequency of negative gaps from 2008 to 2009, both in absolute terms and in terms of frequency per month. Plausible explanations for this surprising finding include the positive trend and lower volatility environment during 2009.

Figure 2: Gap Sizes in Relation to Company Sizes, Adjusted for Illiquid Observations



The pie-charts above graphically show how gap size generally decreases as company size increases with the adjacent number to the pie-charts representing observed gaps per size-group. A detailed table is available in Appendix B

[28] Detailed data on the distribution of gaps from year 2000 through 2010 can be found in Table B2 in Appendix B.

(Table B3). This is in line with previous results showing how larger companies experience less number of gaps. However, as we define gap-size in relative terms subject to price, a stock with a higher stock price will require a larger gap in absolute terms in order to qualify for the mid-size and large-size groups. The charts also show how number of gaps decreases with company size.

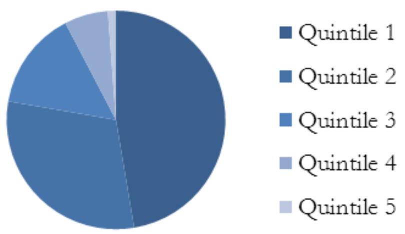
Table B4 in Appendix B compares the gap prevalence in the sub-portfolios of the momentum portfolio, the observations outside of the momentum portfolio and with all observations. The table shows a slightly higher monthly frequency of negative gaps in the loser portfolio compared to the winning portfolio, whereas the winner portfolio has had a higher frequency of positive gaps. This is in line with prevailing theories on how the loser portfolio is supposed to keep underperforming the winner portfolio, thus the annotation momentum. In summary, the momentum portfolio presents slightly fewer gap events occurring on a monthly basis as supposed to observations not included in either the loser or winner portfolio. However, the difference is not large enough in order to make any conclusions.

Before calculating the returns and abnormal returns and running our regressions, previously described corrective actions for illiquidity have been taken. What we find is that a fair share (19.7%) of our observations is deemed illiquid and thus removed.

Figure 3: Review of Observations Deemed Illiquid

Presence of Illiquidity across Company Sizes

Size	Observations omitted due to illiquidity
Quintile 1	60 911
Quintile 2	38 414
Quintile 3	19 382
Quintile 4	7 804
Quintile 5	1 368
Total	127 879



In Figure 3 it is evident how the problem of illiquidity is far likelier to occur for small companies. Of the total number of observations not considered liquid enough for our analysis, almost half occurs within the lowest size quintile. Together, the smallest 40% of companies account for more than 45% of all illiquid observations, whereas the largest quintile of companies account for just around 1% of the illiquid observations.

Next, we study where the returns from price gaps seem to exist. This is done through comparing 1 to 5 days holding periods after a price gap signal whilst looking at different firm market capitalizations and gap sizes for both positive and negative gaps.

Table 1: Returns Following a Gap – Illiquidity Adjusted

Overview of Returns Following a Gap							
Gap type	Holding period	Observations	Mean return	Std.dev.	Number of positive returns	Number of zero returns	Number of negative returns
Positive gaps	1 Day	21 599	0.22%	3.73%	9 582	2 287	9 730
	2 Days	21 592	0.29%	5.02%	9 994	1 547	10 051
	3 Days	21 591	0.31%	5.98%	10 087	1 241	10 263
	4 Days	21 590	0.40%	6.74%	10 292	1 072	10 228
	5 Days	21 588	0.42%	7.48%	10 370	994	10 224
Negative gaps	1 Day	18 542	0.19%	3.82%	8 704	1 952	7 886
	2 Days	18 536	0.23%	5.30%	9 035	1 303	8 198
	3 Days	18 536	0.25%	6.36%	9 098	1 096	8 342
	4 Days	18 528	0.26%	7.09%	9 094	941	8 493
	5 Days	18 523	0.33%	7.76%	9 275	855	8 393

Table 1 shows a brief description of returns following a gap, a detailed table can be found in Table B5, Appendix B. What can be seen is that, on average, returns seem to be positive following a gap disregarding whether the gap is of positive or negative nature. The returns also seem to be high on average, the one day return of a long position in a stock having experienced a positive gap is 0.22% and if the stock has experienced a negative gap the average return is 0.33%. We can also see that the winning rate for positive gaps (negative gaps), measured as the percentage of positive (negative) returns relative to number of zero and negative (positive) returns is below 50%. This means that the strategy generates relatively more losing and neutral trades than winning trades. Furthermore, the standard deviation of the returns seems to increase with increased holding period, which seems reasonable given that returns should vary more over longer holding periods.

MAPPING OF ABNORMAL RETURNS

The graphs under Appendix C maps the abnormal returns following a positive or negative gap for the two risk-adjusting models used throughout this study. Illiquid observations are not included in the charts. The most important findings are that abnormal returns following positive gaps are nearly exclusively positive, disregarding of both gap size and company size, whereas abnormal returns following negative gaps are negative in general following small-sized gaps but varies following mid-sized or large-sized gaps. For small sized negative gaps, abnormal returns seems to be negative for all holding periods for company size quintiles 1-4, where 5 stands out showing positive abnormal returns. Other important findings include the magnitude of the abnormal returns and the magnitude of the standard deviations, repetitively reaching over 50% on a monthly basis. These notable magnitudes may be explained from the fact that price gaps may occur as stocks experience a period of high volatility, and the high abnormal returns would reflect this fact. The abnormal returns on a monthly basis seem to be highest for a holding period of one day. Holding periods of five days seem to generate the least abnormal returns recalculated to monthly values. Looking closer at abnormal returns and company size, no backed conclusions can be made as the distribution of abnormal returns across company sizes seems inconsistent.

In Table C1 and Table C2 we provide detailed descriptions of the abnormal returns from our strategy of buying after positive gaps and short-selling after negative gaps, also including transaction costs and standard deviations. Transaction costs are assumed of being 0.03% per transaction.[29] From the table we find that taking a long position after a positive gap seems profitable on average, even after taking transaction costs into account. However, short-

[29] Transaction costs are estimated with reference to stockbroker Avanza. When computing transaction cost adjusted returns, transactions costs are taken into account both in the buy phase and in the sell phase.

selling on negative gaps generally yields a negative return when taking transaction costs into account. Looking at gap-size, the far largest returns are found in the largest gap-size group, where also the highest standard deviations are found. Abnormal returns, recalculated to monthly values, reaches above 13% for a holding period of one day and for large positive gaps, adjusted for transaction costs. In general, abnormal returns of 2-4% per month are obtained from trading at positive gaps. The highest abnormal returns obtained from our strategy for negative gaps is less than 3%, seen for small size gaps and a holding period of two days. The inclusion of transaction costs is shown to carry the highest level of impact for strategies of one day holding period, explained by the fact that these strategies demand daily trading and hence daily transaction costs.

REGRESSIONS RESULTS

The regression results are presented in Appendix D. Three regression models have been run, each model for combinations of positive and negative gaps with the CAPM model and the Momentum-Extended model. The significance level is shown by *t*-statistics. Heteroskedasticity-robust regressions have been run in order to correct for varying variance of the error term given the explanatory variables.

The results from the regression I in Table D1 show that the event of a positive gap can explain subsequent abnormal returns on a significance level of 1%, showed by *t*-statistics with absolute values of above 2.54, for holding periods of one to five days. The significance persists when taking the momentum factors into account, though the significance, measured by *t*-values, decreases. When sorting gaps into gap sizes in regression II, Table D2 shows how positive gaps in the large gap group are all significant on the 10% level, with absolute values of the *t*-statistics of above 1.64, where significance levels for one day holding period is still on the 1% level for all gap sizes, and for two days on the 5% level. Significance levels generally seem to decline with company size and holding period. The rational for why the significance levels for large gaps are so much smaller could be the high standard deviation in that sub-population. Declining significance for increased holding periods should be expected, as the impact of other explanatory factors increase. After having taken the momentum effect into consideration, positive gaps are only significant for 1 day holding period for large gaps, and not significant for holding period of 2-5 days. For small- and mid-sized gaps, the event is still significant on the 1% level for all holding period, though with lower *t*-statistics as compared to the model not taking the momentum effect into account.

In Regression III, controls for company size is also included. While controlling for company size, negative small gaps are now significant on a 5% level for a holding period of one day, and on a 1% significance level for holding periods of 2-5 days, using both the CAPM and the Momentum-Extended model. This is in line with the graphs showed under Appendix C, where we found that small-sized gaps seemed to be associated with subsequent negative abnormal returns. For negative gaps, controlling for company size hence seems to enhance the explanatory power. The inclusion of company size does not seem to enhance the explanatory power for positive gaps in the same manner.

From the regressions, universally very low values for R-squared are found. This indicates that gaps only explain a small fraction of the variance in abnormal returns. Considering all factors not included in the models that may explain stock movements, and their explanatory power in relation to price gaps', this seems reasonable.

VI CONCLUSION

This study has examined the hypotheses that there is a price continuation effect after inter-day positive and negative price gaps. Using Swedish stock data from January 1, 2000 through December 31, 2010 we have examined whether profitable trading could arise from buying stocks after a positive price gap and short-selling stocks having experienced a negative price gap. In line with our hypothesis, we have found support of a continued rise in stock price following a positive inter-day price gap. More specifically, buying stocks after these events seems to generate positive abnormal returns in the short term, even after taking transaction costs into account. The same support was not found for negative gaps. Overall, negative gaps showed ambiguous results and did not prove significant in explaining abnormal returns. However, the sub-section of small size gaps for negative gaps proved significant on the 5% level in explaining abnormal returns, for all holding periods and when using both risk-adjusting models. This section aims to discuss these results and their implications.

The main characteristics of price gaps have been mapped. We have found that the profitability of acting on price gaps seems to be highest in positive large gaps (>2.0%) and a holding period of 1 day. In compliance with the high returns we have also found correspondingly high standard deviations, which is a measure of risk. The general idea within finance is that the potential of high returns should be accompanied with high risk, a criteria seemingly fulfilled for price gaps.

Even when correcting for risk there seems to be positive abnormal returns left for positive gaps, whereas the abnormal returns following negative gaps vary depending on company size and gap size. These ambiguous results indicate that negative gaps does not explain abnormal returns in the same way. From using two models in order to risk-adjust our returns, we believe to have found a substantial portion of the returns that is explained by increased risk taking. Still, a potential caveat with this study is the insufficient use of risk-explanatory variables. More comprehensive models would likely lower magnitudes on abnormal returns following price gaps. The use of the momentum portfolio on a daily basis is furthermore something that is not commonly practiced to our knowledge, but as the inclusion of the momentum factor decreases observed abnormal returns this indicates that the momentum strategy does explain part of abnormal returns for the phenomena of price gaps.

In order to obtain a better understanding of why this price continuation for positive gaps occurs, theories within behavioral finance could be applied. Assuming that one potential origin of price gaps is due to new information, the disequilibrium model would argue that this new information would cause supply and demand imbalances for the stock, leading to a delay in the process of finding the fundamental equilibrium price and subsequently to increased volatility. According to the conservatism bias this new information is likely undervalued and slowly updated in the mindset of investors. Together with the information diffusion model, stating that investors obtain information gradually, this would result in an underreaction from investors and consequently the price continuation we have observed following positive gaps. From the nature of gaps, it is reasonable to expect that gaps occur in especially volatile stocks or in especially volatile periods for companies, a belief confirmed by the high standard deviations seen in the analysis. An increase in volatility would, according to Zhang (2006), strengthen a price continuation effect. This theory could help to explain the exceptionally high abnormal returns found and why they persist even as we control for the momentum effect. Another applicable theory when explaining the price continuation after positive gaps is the theory on positive feedback rules, the trend-chasing behavior of investors to buy as prices rise, which would further push prices upward. Also, the representativeness heuristic may help to explain why prices tend to continue rising after a price gap. Investors overestimate the representativeness of a gap and thereby anticipate a continued strong performance after the event. The herding behavior of investors is often described with the metaphor "Don't miss the train when it leaves the train station", explaining the tendency of investors to buy rising stocks and thus contributing to the price-continuation effect observed in connection with price gaps. Though many theories may explain the found price continuation, we do not find the theory of self-fulfillment of technical analysis strategies to be plausible in this case because of probable unfamiliarity of the price gap pattern among investors.

Our finding on how negative gaps does not seem to explain the abnormal returns that follows in the same manner as positive gaps, could be explained by the disposition effect. That is, investors' tendency to keep losing positions when stocks are falling. Had they, in theory, sold after a negative price gap the stock price would likely fall further and thus create a price continuation effect.

According to our findings, a previously not explored nor discussed anomaly seems to exist. The implications of this is that we find evidence against the weak-form of the efficient market hypothesis, and that information in past prices can help predicting stock movements. Our findings gives support to the words of Pablo Picasso-

"Action is the foundational key to all success".

VII FUTURE RESEARCH

Though extensive research have been conducted in the field of technical analysis, research on the phenomena of price gaps, discussed in this thesis, is very limited. With this study we sought to arouse interest in a virtually unexplored pattern, and we believe that further research is needed to better understand the nature of price gaps. The choices made in terms of data adjustments and model specification may have carried large impact on our analysis. Thus with different assumptions and approaches different results may arise. Suggestions to future research set-ups is to incorporate e.g. stop-loss strategies, study other regional areas, take volume into account and include extended models for risk-adjusting returns.

REFERENCES

Agyei-Ampomah, S. (2007), "The Post-Cost Profitability of Momentum Trading Strategies: Further Evidence from the UK", *European Financial Management,* **13**(4), 776-802.

Alexander, S.S. (1964), “Price Movements in Speculative Markets: Trends or Random Walks, No. 2”, *Industrial Management Review,* **5**(1), 7-26.

Ali, A., Trombley, M.A. (2006), “Short Sales Constraints and Momentum in Stock Return”, *Journal of Business Finance and Accounting,* **33**(3-4), 587-615.

Bachelier, L. (1900), “Théorie de la Spéculation”, *Annales Scientifiques de l'École Normale Supérieure, série 3. 17:21-86,* Translated in Paul. H. Cootner, 1964. *The Random Character of Stock Market Prices.* Cambridge, MA: MIT Press.

Badrinath, S.G., Wahal, S. (2002), “Momentum Trading by Institutions”, *Journal of Finance,* **57**(6), 2449-2478.

Banerjee, A.V. (1992), “A Simple Model of Herd Behavior”, *The Quarterly Journal of Economics,* **107**(3), 797-817.

Barberis, N., Shleifer, A., Vishny, R. (1998), “A Model of Investor Sentiment”, *Journal of Financial Economics,* **49**(3), 307-343.

Barberis, N., Shleifer, A. (2003), “Style Investing”, *Journal of Financial Economics,* **68**(2), 161-199.

Beja, A., Goldman, M.B. (1980), “On the Dynamics of Behavior of Prices in Disequilibrium”, *Journal of Finance,* **35**(2), 235-248.

Bigalow, S. (2002), “Profitable Candlestick Trading: Pinpointing Market Opportunities to Maximize Profits”, New York: John Wiley and Sons.

Black, F. (1993), “Beta and Return”, *Journal of Portfolio Management,* **20**(1), 8-18.

Brock, W., Lakanishok, J., LeBaron, B. (1992), “Simple Technical Trading Rules and the Stochastic Properties of Stock Returns”, *Journal of Finance,* **48**(5), 1731-1764.

Caginalp, G., Laurent, H. (1998), “The Predictive Power of Price Patterns”, *Applied Mathematical Finance,* **5**(3-4), 181-205.

Chui, A., Titman, S., Wei, K.C.J. (2010), “Individualism and Momentum Around the World”, *Journal of Finance,* **65**(1), 361-392.

Conrad, J., Kaul, G. (1998), “An Anatomy of Trading Strategies”, *Review of Financial Studies,* **11**(3), 489-519.

Cowles, A. (1933), “Can Stock Market Forecasters Forecast?”, *Econometrica,* **1**(3), 309-324.

Daniel, K., Hirshleifer, D., Subrahmanyam, A. (1998), “Investor Psychology and Security Market under- and overreactions”, *Journal of Finance,* **53**(6), 1839-1885.

De Bondt, W.F.M., Thaler, R. (1985), ”Does the Stock Market Overreact?”, *Journal of Finance,* **40**(3), 793-805.

De Bondt, W.F.M., Thaler, R. (1987), ”Further Evidence on Investor Overreaction and Stock Market Seasonality”, *Journal of Finance,* **42**(3), 557-581.

De Long, B.J., Shleifer, A., Summers, L.H., Waldmann, R.J. (1990), "Noise Trader Risk in Financial Markets", *Journal of Political Economy,* **98**(4), 703-738.

Edwards, W. (1968), "Conservatism in Human Information Processing", *Formal Representation of Human Judgment,* Edited by Kleinmuntz, B., New York: Wiley. 17-52.

Fama, E.F., Blume, M. (1966), "Filter Rules and Stock Market Trading", *Journal of Business,* **39**(1), 226-241.

Fama, E.F. (1970), "Efficient Capital Markets: A Review of Theory and Empirical Work" *Journal of Finance,* **25**(2), 383-417.

Fama, E., French, K. (1996), "Multifactor Explanations of Asset Pricing Anomalies", *Journal of Financial Economics,* **51**(1), 55-84.

Fiess, N., MacDonald, R. (2002), "Towards the Fundamentals of Technical Analysis: Analysing the Information Content of High, Low and Close Prices", *Economic Modeling,* **19**(3), 353-374.

Fischer, R., Fisher, J. (2003), "Candlesticks, Fibonacci and Chart Pattern Trading Tools: A Synergistic Strategy to Enhance Profits and Reduce Risk", New York: John Wiley and Sons.

Fock, J.H., Klein, C., Zwergel, B. (2005), "Performance of Candlestick Analysis on Intraday Futures Data. *Journal of Futures Markets,* **13**(1), 28-40.

Froot, K.A., Scharfstein, D.S., Stein, J.C. (1992), "Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation", *Journal of Finance,* **47**(4), 1461-1484.

Goo, Y-J., Chen, D-H., Chang, Y-W. (2007), "The Application of Japanese Candlestick Trading Strategies in Taiwan", *Investment Management and Financial Innovations,* **4**(4), 49-71.

Griffin, J.M., Ji, X., Martin, J.S. (2003), "Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole", *Journal of Finance,* **58**(6), 2515-2547.

Griffioen, G.A.W. (2003), "Technical Analysis in Financial Markets", PhD Thesis, University of Amsterdam.

Grinblatt, M., Titman, S., Wermers, R. (1995), "Momentum Investment Strategies, Portfolio Performance, and Herding: a Study of Mutual Fund Behavior", *American Economic Review,* **85**(5), 1088-1105.

Grinblatt, M., Han, B. (2005), "Prospect Theory, Mental Accounting, and Momentum, *Journal of Financial Economics,* **78**(2), 311-339.

Grundy, B.D., Martin, S.J. (2001), "Understanding the Nature of Risks and the Sources of Rewards to Momentum Investing", *Review of Financial Studies,* **14**(1), 29-78.

Hamilton, W.P. (1922), "The Stock Market Barometer", New York: Harper & Brothers, Reprint in 1998, New York: John Wiley & Sons.

Hanna, J.D., Ready, M. (2005), "Profitable Predictability in the Cross Section of Stock Returns", *Journal of Financial Economics,* **78**(3), 463-505.

Hong, H.G., Stein, J.C. (1999), "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets", *Journal of Finance,* **54**(6), 2143-2184.

Horton, M.J. (2009), "Stars, Crows and Doji: The Use of Candlesticks in Stock Selection", *Quarterly Review of Economics and Finance,* **49**(2), 283-294.

Jegadeesh, N. (1990), "Evidence of Predictable Behavior of Security Returns", *Journal of Finance,* **45**(3), 881-898.

Jegadeesh, N., Titman, S. (1993), "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency", *Journal of Finance,* **48**(1), 65-91.

Jegadeesh, N., Titman, S. (2001), "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations", *Journal of Finance,* **56**(2), 699-720.

Jeegadeesh, N., Titman, S. (2011), "Momentum", *Annual Review of Financial Economics,* **3**(1), 493-509.

Jensen, M.C. (1978), "Some Anomalous Evidence Regarding Market Efficiency", *Journal of Financial Economics,* **6**(2-3), 95-101.

Kendall, D.G. (1953), "Stochastic Processes Occurring in the Theory of Queues and their Analysis by the Method of the Imbedded Markov Chain", *Annals of Mathematical Statistics*, **24**(3), 338-354.

Korajczyk, R.A., Sadka, R. (2004), "Are Momentum Profits Robust to Trading Costs?", *Journal of Finance,* **59**(3), 1039-1082.

Laknishok, J., Shleifer, A., Vishny, R. (1994), "Contrarian Investment, Extrapolation, and Risk", *Journal of Finance,* **49**(5), 1541-1578.

Lehmann, B. (1990), "Fads, Martingales, and Market Efficiency", *Quarterly Journal of Economics,* **105**(1), 1-28.

Lesmond, D.A., Schill, M.J., Zhou, C. (2004), "The Illusory Nature of Momentum Profits", *Journal of Financial Economics,* **71**(2), 349-380.

Li, X., Miffre, J., Brooks, C., O'Sullivan, N. (2008), "Momentum Profits and Time-Varying Unsystematic Risk", *Journal of Banking and Finance,* **32**(4), 541-558.

Lintner, J. (1965), "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets", *Review of Economics and Statistics,* **47**(1), 13-37.

Lo, A., Mamaysky, H., Wang, J. (2000), "Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation", *Journal of Finance,* **55**(4), 1705-1770.

Lo, A. (2004), "The Adaptive Market Hypothesis: Market Efficiency from an Evolutionary Perspective", *Journal of Portfolio Management,* **30**(1), 15-29.

Lu, T-H., Shiu, Y-M., Liu, T-C. (2012), "Profitable Candlestick Trading Strategies – The Evidence from a New Perspective", *Review of Financial Economics,* **21**(2), 63-68.

MacKinlay, A.C. (1995), "Multifactor Models do not Explain Deviations from the CAPM", *Journal of Financial Economics,* **38**(1), 3-28.

Malkiel, B.G. (1973), "A Random Walk Down Wall Street", New York: W.W. Norton & Company.

Malkiel, B.G. (2011), "A Random Walk Down Wall Street", (Revised Edition), New York: W.W. Norton & Company.

Mandelbrot, B. (1966), "Forecasts of Future Prices, Unbiased Markets, and 'Martingale' Models", *Journal of Business,* **39**(1, Special Supplement), 242-255.

Marshall, B.R., Young, M.R., Rose, L.C. (2006), "Are Candlestick Technical Trading Strategies Profitable in the Japanese Equity Market?", *Review of Quantitative Finance & Accounting,* **31**(2), 191-207.

Marshall, B.R., Young, M.R., Rose, L.C. (2007), "Market Timing with Candlestick Technical Analysis", *Journal of Financial Transformation,* **20**(1), 18-25.

Marshall, B.R., Young, M.R., Rose, L.C. (2008), "Candlestick Technical Trading Strategies: Can They Create Value for Investors?", *Journal of Banking & Finance,* **30**(8), 2303-2323.

Menkhoff, L., Taylor, M.P. (2007), "The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis", *Journal of Economic Literature,* **45**(4), 936-972.

Morris, G. (1995), "Candlestick Charting Explained: Timeless Techniques for Trading Stocks and Futures, 2nd Edition", New York: McGraw-Hill Trade.

Mulvey, J.M., Kim, W.C. (2008), "Active Equity Managers in the US: Do the Best Follow Momentum Strategies?", *Journal of Portfolio Management,* **34**(2), 126-134.

Nison, S. (1991), "Japanese Candlestick Charting Techniques: A Contemporary Guide to the Ancient Investment Techniques of the Far East", New York: New York Institute of Finance.

Nison, S. (1994), "Beyond Candlesticks: New Japanese Charting Techniques Revealed", New York: Wiley and Sons.

Odean, T. (1998), "Are Investors Reluctant to Realize their Losses?", *Journal of Finance,* **53**(5), 1775-1798.

Okamoto, H. (2003), "Practical Utilization of Japanese Technical Charts", Presented at the TA Forum, Paris, March 22.

Park, C-H., Irwin, S.H. (2004), "The Profitability of Technical Analysis: A Review", AgMAS Project Research Report. University of Illinois at Urbana-Champaign.

Pring, M. (2002), "Candlesticks Explained", New York: McGraw-Hill.

Regnault, J. (1863), "Calcul des Chances et Philosophie de la Bourse", Paris: Mallet Bachelier & Castel (Bibliothèque Nationale, Paris, Inventaire V.51.066).

Rhea, R. (1932), "The Dow Theory", New York: Barron's, Reprint in 1993, Burlington: Fraser Publishing Company.

Roberts, H.V. (1959), "Stock-Market "Patterns" and Financial Analysis: Methodological Suggestions", *Journal of Finance,* **14**(1), 1-10.

Rouwenhorst, K. G. (1998), "International Momentum Strategies", *Journal of Finance,* **53**(1), 267-284.

Samuelson, P.A. (1965), "Proof That Properly Anticipated Prices Fluctuate Randomly", *Industrial Management Review,* **6**(2), 41-49.

Schiereck, D., De Bondt, W., Weber, M. (1999), "Contrarian and Momentum Strategies in Germany", *Financial Analysts Journal,* **55**(6), 104-116.

Schulmeister, S. (2006), "The Interaction Between Technical Currency Trading and Exchange Rate Fluctuations", *Finance Research Letters,* **3**(3), 212-233.

Schulmeister, S. (2007), "The Interaction Between the Aggregate Behavior of Technical Trading Systems and Stock Price Dynamics", WIFO Working Paper.

Schwert, G.W. (2003), "Anomalies and Market Efficiency", In Constantinides, G., Harris, M., Stultz, M. (Eds.), *Handbook of the Economics of Finance,* Amsterdam: Elsevier, 937-972.

Sharpe, W. (1964), "Capital Asset Prices: A Theory of Market Equilibrium", *Journal of Finance,* **19**(3), 425-442.

Shefrin, H., Statman, M. (1985), "The Disposition to Sell Winners too Early and Ride Losers too Long: Theory and Evidence", *Journal of Finance,* **40**(3), 777-791.

Shiu, Y-M., Lu, T-H. (2011), "Pinpoint and Synergistic Trading Strategies of Candlesticks", *International Journal of Econonomics and Finance,* **3**(1), 234-244.

Sullivan, R., Timmermann, A., White, H. (1999), "Data Snooping, Technical Trading Rules Performance, and the Bootstrap", *Journal of Finance,* **54**(5), 1647-1691.

Sweeney, R. (1986), "Beating the Foreign Exchange Market", *Journal of Finance,* **41**(1), 163-182.

Tversky, A., Kahneman, D. (1974), "Judgment Under Uncertainty: Heuristics and Biases", *Science,* **185**(4157), 1124-1131.

Wagner, G.S., Matheny, B.L. (1993), "Trading applications of Japanese Candlestick Charting", New York: John Wiley and Sons.

Wang, K-Y., Peng, S-C., Huang, Y-S. (2009), "The Intraday Performance of Contrarian Strategies: Evidence from the Taiwan Stock Exchange", *Review of Pacific Basin Financial Markets and Policies,* **12**(4), 655-674.

Working, H. (1934), "A Random-Difference Series for Use in the Analysis of Time Series", *Journal of the American Statistical Association,* **29**(185), 11-24.

Working, H. (1949), "The Investigation of Economic Expectations", *American Economic Review,* **39**(3), 150-166.

Zhang, X.F. (2006), "Information Uncertainty and Stock Returns", *Journal of Finance,* **61**(1), 105-136.

Appendices

Appendix A: Explanatory Illustrations

Figure A1: Price Continuation Hypothesis

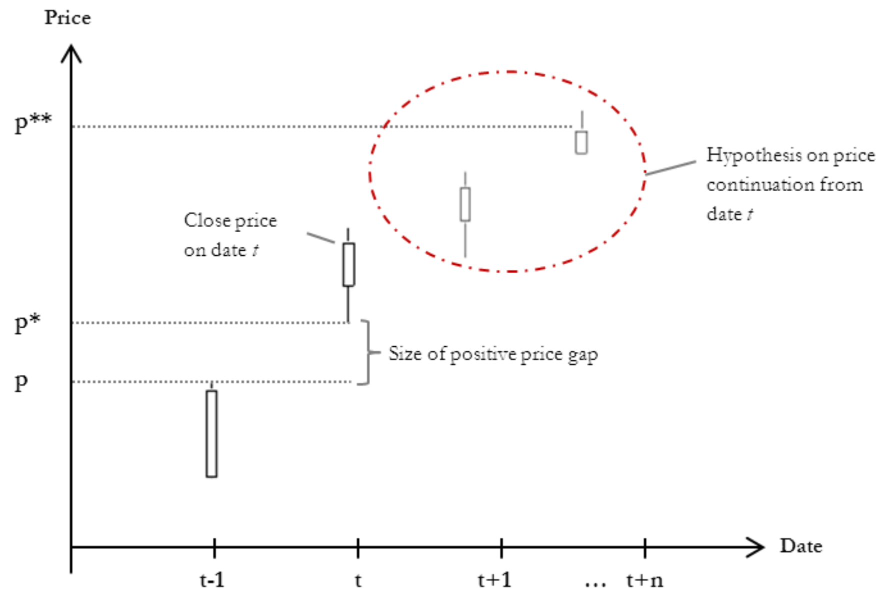


Figure A1 illustrates the hypothesis of price continuation in the direction of the gap, in this case a positive gap occurring from day *t-1* to *t*. The lowest traded price during day *t* is higher than day *t-1*'s highest trading price. The gap is confirmed at day *t*'s close. According to our hypothesis we expect prices to continue to rise at day *t+1* until *t+n*. The proposed trading strategy is to buy at the close of trading day *t* and selling at trading day *t+n*.

Figure A2. Illustration of Positive and Negative Price Gap Signals

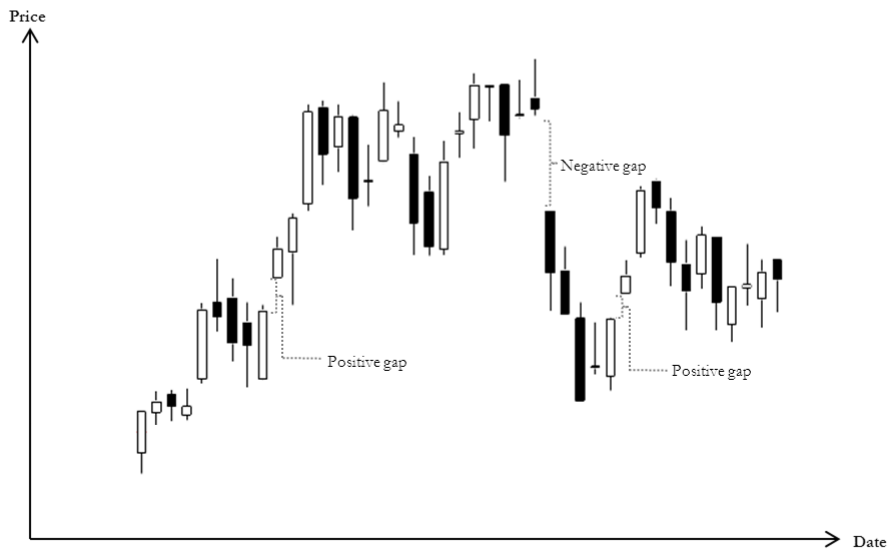
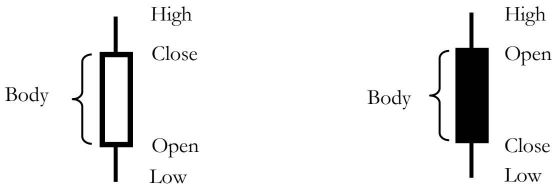


Figure A2 illustrates different sizes of price gaps and the difference between positive and negative gaps. Every candle represents one trading day. A black candle indicates a negative close on the day and a white candle indicates a positive close.

Figure A3. Candlestick Components



Illustrations of the components of a candlestick. If the close price of a trading day *t+1* is higher (lower) than the previous trading day *t*'s close price the body will be white (black).

APPENDIX B: DESCRIPTIVE STATISTICS

Table B1: Overview of Gap Characteristics across Company Sizes

Summary over Gap Characteristics

			Company Size				
All observations		All	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
All gaps	Events	70 118	21 750	17 938	13 793	9 545	7 092
	Frequency	2.15	3.61	2.91	2.16	1.49	1.11
	Mean size	1.70%	2.33%	1.89%	1.60%	1.50%	1.19%
	Std. Dev.	2.21%	2.95%	2.37%	2.02%	2.23%	1.96%
Positive gaps	Events	35 600	10 376	9 003	7 142	5 105	3 974
	Frequency	1.09	1.72	1.46	1.12	0.80	0.62
	Mean size	1.71%	2.15%	1.81%	1.54%	1.38%	1.06%
	Std. Dev.	2.35%	2.67%	2.39%	2.10%	2.17%	1.70%
Negative gaps	Events	34 518	11 374	8 935	6 651	4 440	3 118
	Frequency	1.06	1.89	1.45	1.04	0.69	0.49
	Mean size	1.70%	2.06%	1.71%	1.56%	1.35%	1.14%
	Std. Dev.	2.06%	2.56%	1.79%	1.72%	1.58%	1.71%
Liquid observations							
All gaps	Events	40 156	7 243	9 199	9 296	7 691	6 727
	Frequency	1.53	2.04	2.00	1.67	1.25	1.05
	Mean	1.33%	1.54%	1.48%	1.33%	1.21%	1.02%
	Std. Dev.	1.90%	2.23%	2.09%	1.61%	1.81%	1.62%
Positive gaps	Events	21 609	3801	4875	4983	4160	3790
	Frequency	0.82	1.07	1.06	0.89	0.68	0.59
	Mean size	1.36%	1.62%	1.57%	1.34%	1.21%	1.00%
	Std. Dev.	2.05%	2.20%	2.46%	1.73%	2.05%	1.61%
Negative gaps	Events	18 547	3 442	4 324	4 313	3 531	2 937
	Frequency	0.71	0.97	0.94	0.77	0.58	0.46
	Mean size	1.29%	1.45%	1.38%	1.32%	1.20%	1.06%
	Std. Dev.	1.69%	2.25%	1.57%	1.45%	1.48%	1.62%
Illiquid observations							
All gaps	Events	29 962	14 507	8 739	4 497	1 854	365
	Frequency	4.75	4.84	4.64	4.65	4.76	5.34
	Mean size	2.21%	2.38%	2.05%	2.01%	2.04%	2.49%
	Std. Dev.	2.49%	2.75%	2.09%	2.39%	2.20%	2.50%
Positive gaps	Events	13 991	6 575	4 128	2 159	945	184
	Frequency	2.22	2.19	2.19	2.23	2.42	2.69
	Mean size	2.26%	2.46%	2.08%	2.00%	2.16%	2.49%
	Std. Dev.	2.05%	2.87%	2.26%	2.72%	2.51%	2.57%
Negative gaps	Events	15 971	7 932	4 611	2 338	909	181
	Frequency	2.53	2.64	2.45	2.42	2.33	2.65
	Mean size	2.17%	2.32%	2.02%	2.01%	1.91%	2.48%
	Std. Dev.	1.69%	2.64%	1.93%	2.05%	1.82%	2.43%

In table B1 , an overview is provided on where gaps occur. First, gaps across the entire dataset is displayed followed by separate tables for liquid and illiquid observations. Events is the number of gaps. Frequency is measured in average number of events per month per stock, calculated with the assumption that each month has 20 trading days. Companies are divided into quintiles based on company size, measured with company market capitalization and updated on a yearly basis. Mean size displays the average size of the gap, as defined under Section I. Std.Dev is the standard deviation of these sizes.

Table B2: Yearly Incidence of Gaps Over the Time-Period

Gap Distribution per Year									
	Positive Gaps			Negative Gaps			All Gaps		
Year	Events	Percent of total	Mean size	Events	Percent of total	Mean size	Events	Percent of total	Mean size
2000	2456	6.90%	1.96%	2586	7.49%	1.89%	5042	7.19%	1.93%
2001	3166	8.89%	2.40%	3395	9.84%	2.44%	6561	9.36%	2.42%
2002	3809	10.70%	2.75%	4304	12.47%	2.68%	8113	11.57%	2.71%
2003	4340	12.19%	2.12%	3662	10.61%	2.09%	8002	11.41%	2.11%
2004	3801	10.68%	1.31%	3437	9.96%	1.30%	7238	10.32%	1.31%
2005	3280	9.21%	1.05%	2512	7.28%	1.01%	5792	8.26%	1.03%
2006	3280	9.21%	1.11%	3044	8.82%	1.09%	6324	9.02%	1.10%
2007	3047	8.56%	1.18%	3455	10.01%	1.07%	6502	9.27%	1.12%
2008	3205	9.00%	1.79%	4320	12.52%	1.62%	7525	10.73%	1.69%
2009	2973	8.35%	1.58%	2085	6.04%	1.48%	5058	7.21%	1.54%
2010	2243	6.30%	1.22%	1718	4.98%	1.22%	3961	5.65%	1.22%

Table B2 shows how the number of gaps differ across the time-period, where Events is the number of gaps for each respective year. Percent of total displays the percent of all gaps that occurred during a specific year. Mean size displays the average size of a gap for that year. Illiquid observations are not excluded in the data in the table.

Table B3: Summary of Gap Sizes

Summary Statistics over Gap Sizes							
			Company Size				
		All	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
All gaps	Events	70 118	21 750	17 938	13 793	9 545	7 092
	Mean size	1.7%	2.1%	1.8%	1.6%	1.4%	1.1%
	Std. dev.	2.2%	2.6%	2.1%	1.9%	1.9%	1.7%
Positive gaps	Events	35 600	10 376	9 003	7 142	5 105	3 974
	Mean size	1.7%	2.2%	1.8%	1.5%	1.4%	1.1%
	Std. dev.	2.4%	2.7%	2.4%	2.1%	2.2%	1.7%
Negative gaps	Events	34 518	11 374	8 935	6 651	4 440	3 118
	Mean size	1.7%	2.1%	1.7%	1.6%	1.3%	1.1%
	Std. dev.	2.1%	2.6%	1.8%	1.7%	1.6%	1.7%

Table B3 provides an overview of how gap-sizes differ across the different size-quintiles, based on market capitalization. Events is number of observed gaps. Mean size displays the average size of the gap, as defined under Section I. Std.dev. is the standard deviation of the gap sizes in each subgroup. Illiquid observations are not excluded in the data in the table.

Table B4: Gaps in the Momentum Portfolio

Gap Incidence in the Momentum Portfolio				
		Type of Gap		
		Positive gaps	Negative gaps	Total gaps
Momentum portfolio	Observations	6 165	6 065	12 230
	Frequency/ month	1.07	1.05	2.12
- Loser portfolio	Observations	2 970	3 142	6 112
	Frequency/ month	1.03	1.09	2.13
- Winner portfolio	Observations	3 195	2 923	6 118
	Frequency/ month	1.10	1.01	2.11
Gaps outside of the momentum portfolio	Observations	29 435	28 453	57 888
	Frequency/ month	1.15	1.11	2.26
Total	Observations	35 600	34 518	70 118
	Frequency/ month	1.13	1.10	2.23

The table displays the observations, in terms of gaps, and frequency, in terms of observations per month per company, of the loser and winner portfolio constituting the momentum portfolio. The complete momentum portfolio is also shown as well as observations not included outside of the momentum portfolio. Finally, the total dataset is displayed with number of observations and frequency. Illiquid observations are not excluded in the data in the table.

Table B5: Description of Returns Following a Gap

Summary of Trading Returns across Company Sizes for Holding Period 1-5 Days											
		Negative gaps					**Positive gaps**				
Company size	Holding period	Obs.	Mean return	Std. dev.	Min.	Max.	Obs.	Mean return	Std. dev.	Min.	Max.
All	1 Day	18542	0.19%	3.82%	-52.76%	69.40%	21599	0.22%	3.73%	-36.69%	91.49%
	2 Days	18536	0.23%	5.30%	-58.45%	80.33%	21592	0.29%	5.02%	-43.51%	107.03%
	3 Days	18536	0.25%	6.36%	-58.06%	124.18%	21591	0.31%	5.98%	-52.85%	84.33%
	4 Days	18528	0.26%	7.09%	-57.22%	135.29%	21592	0.40%	6.74%	-71.46%	116.33%
	5 Days	18523	0.33%	7.76%	-77.98%	126.47%	21588	0.42%	7.48%	-74.90%	145.92%
Size quintile 1	1 Day	3444	0.25%	4.25%	-48.62%	69.40%	3799	0.35%	4.59%	-31.03%	70.45%
	2 Days	3440	0.24%	5.69%	-44.83%	80.33%	3801	0.53%	6.27%	-27.10%	107.03%
	3 Days	3437	0.25%	7.29%	-45.67%	114.29%	3803	0.56%	7.35%	-52.85%	76.67%
	4 Days	3432	0.20%	8.04%	-51.44%	135.29%	3804	0.61%	8.36%	-49.37%	116.33%
	5 Days	3432	0.07%	8.57%	-77.98%	126.47%	3799	0.50%	9.09%	-49.37%	145.92%
Size quintile 2	1 Day	4321	0.22%	3.74%	-35.46%	28.68%	4879	0.22%	3.83%	-24.70%	47.76%
	2 Days	4317	0.28%	5.16%	-45.04%	47.83%	4880	0.28%	5.29%	-31.25%	79.07%
	3 Days	4322	0.24%	6.15%	-55.32%	56.98%	4879	0.31%	6.27%	-35.94%	84.33%
	4 Days	4325	0.26%	7.10%	-51.77%	92.86%	4879	0.44%	6.95%	-38.28%	71.07%
	5 Days	4323	0.31%	7.65%	-57.09%	71.43%	4881	0.54%	7.99%	-36.20%	101.41%
Size quintile 3	1 Day	4312	0.14%	3.73%	-52.76%	38.17%	4979	0.18%	3.45%	-30.77%	91.49%
	2 Days	4313	0.14%	5.04%	-58.45%	44.93%	4972	0.22%	4.50%	-31.41%	96.81%
	3 Days	4311	0.22%	5.78%	-39.31%	47.37%	4971	0.24%	5.31%	-39.58%	78.72%
	4 Days	4307	0.18%	6.29%	-42.86%	44.93%	4976	0.35%	6.04%	-71.46%	76.60%
	5 Days	4312	0.25%	6.90%	-42.86%	51.58%	4974	0.35%	6.55%	-74.90%	59.57%
Size quintile 4	1 Day	3532	0.10%	3.63%	-20.59%	27.74%	4151	0.25%	3.47%	-36.69%	70.61%
	2 Days	3534	0.13%	5.23%	-29.64%	61.00%	4148	0.32%	4.54%	-43.51%	56.55%
	3 Days	3536	0.16%	6.11%	-32.91%	66.00%	4148	0.38%	5.65%	-44.81%	59.64%
	4 Days	3536	0.20%	6.94%	-33.54%	66.07%	4145	0.46%	6.32%	-61.36%	57.97%
	5 Days	3531	0.34%	7.85%	-38.03%	98.00%	4147	0.52%	7.01%	-57.29%	87.50%
Size quintile 5	1 Day	2933	0.28%	3.76%	-30.41%	31.87%	3791	0.12%	3.19%	-24.51%	32.59%
	2 Days	2932	0.39%	5.45%	-54.44%	65.93%	3791	0.12%	4.35%	-30.68%	36.44%
	3 Days	2930	0.40%	6.58%	-58.06%	124.18%	3790	0.06%	5.22%	-39.83%	42.14%
	4 Days	2928	0.49%	7.18%	-57.22%	71.11%	3788	0.17%	5.90%	-45.66%	49.59%
	5 Days	2925	0.76%	7.98%	-65.00%	93.33%	3787	0.18%	6.60%	-46.03%	66.06%

Obs. shows number of observations of returns for each holding period. Note that there are slightly fewer observations for longer holding periods as longer holding periods require that there is data for the following days, e.g. the following four days for a five-day holding period. Std.dev. is the standard deviation of the returns for a given company quintile and holding period. Min. and Max. displays the minimum and maximum return respectively for each sub-group.
Observations deemed illiquid are excluded in the table.

APPENDIX C: MAPPING OF ABNORMAL RETURNS

Figure C1. Abnormal Returns for Gaps with 1 Day Holding Period

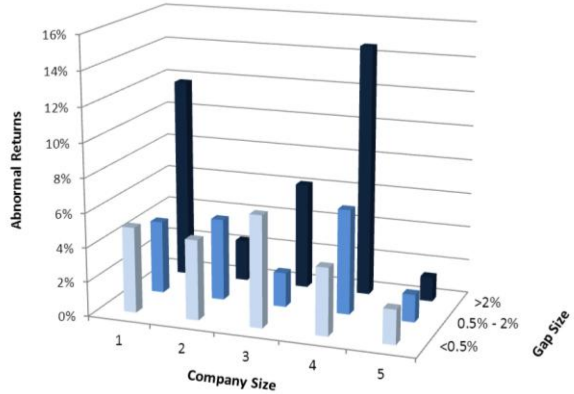
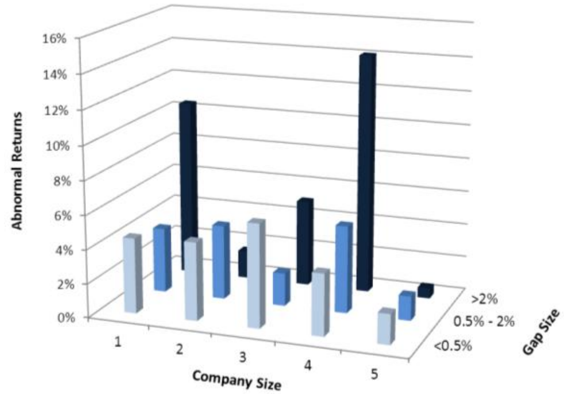
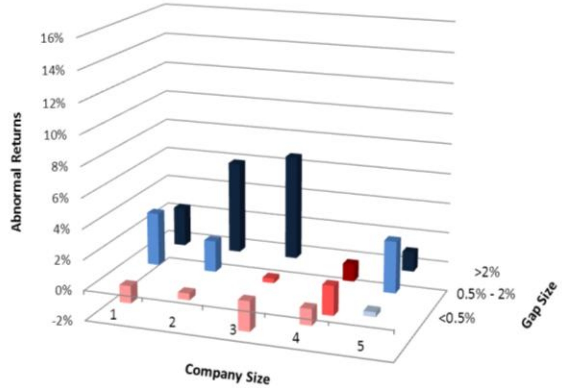
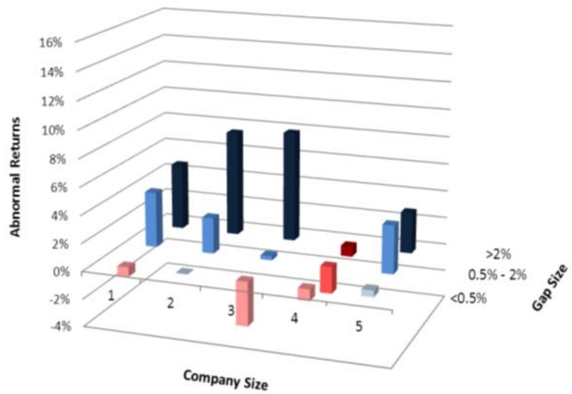
	Risk-Adjusted with CAPM	Risk-Adjusted with CAPM and the Momentum Factor
Positive Gaps		
Negative Gaps		

Figure C1 illustrates the abnormal returns for positive and negative gaps with 1 day holding period. The abnormal 1 month return is shown on the vertical y-axis. The company size, labeled from 1-5 (where group 1 is companies with lowest market capitalization and group 5 is companies with highest market capitalization), is shown on the horizontal x-axis. The gap size, separated in three groups, is shown on the depth axis (z-axis). Abnormal returns taking only the market factor (CAPM) into account in the risk-adjusting process, is shown to the left hand side of the figure. Abnormal returns taking both the market factor (CAPM) and the momentum factor into account in the risk-adjusting process, is shown to the right hand side of the figure. The abnormal returns are adjusted for illiquid stocks. Different shades of blue indicates positive abnormal returns while different shades of red indicates negative abnormal returns.

Figure C2. Abnormal Returns for Gaps with 2 Days Holding Period

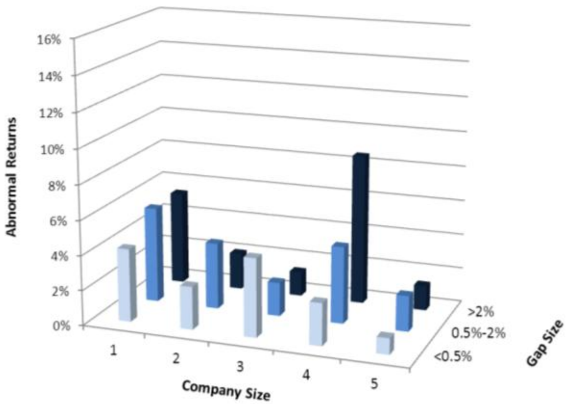
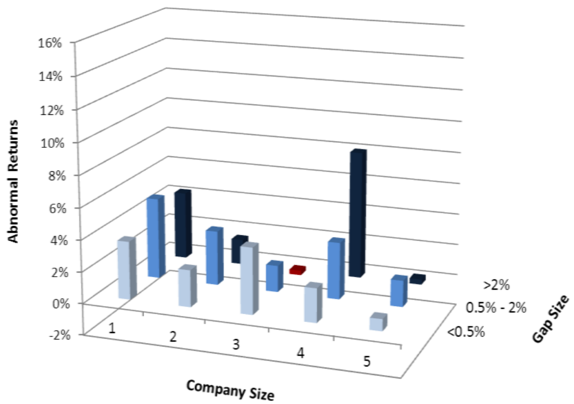
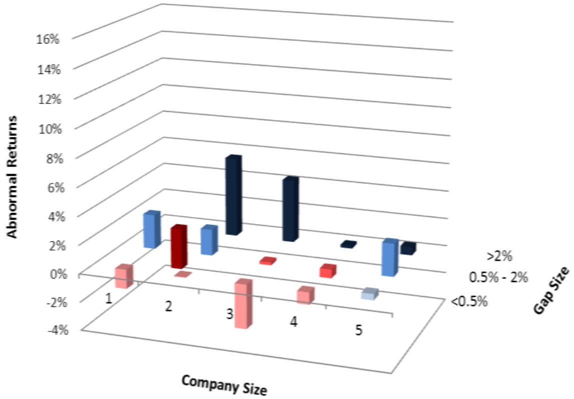
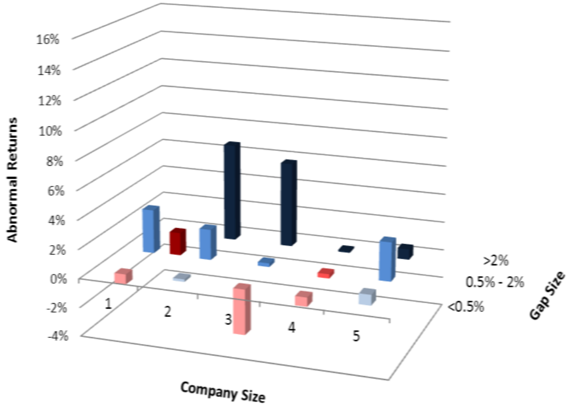
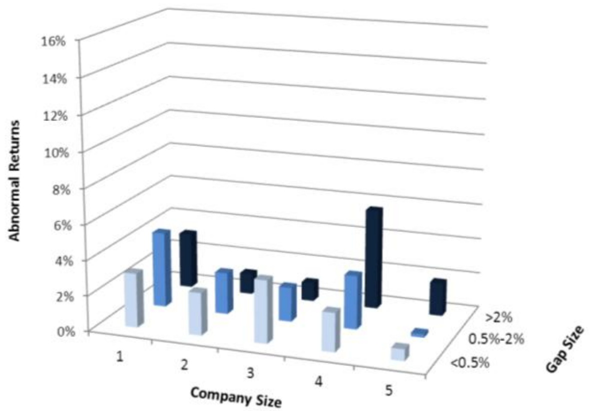
	Risk-Adjusted with CAPM	Risk-Adjusted with CAPM and the Momentum Factor
Positive Gaps		
Negative Gaps		

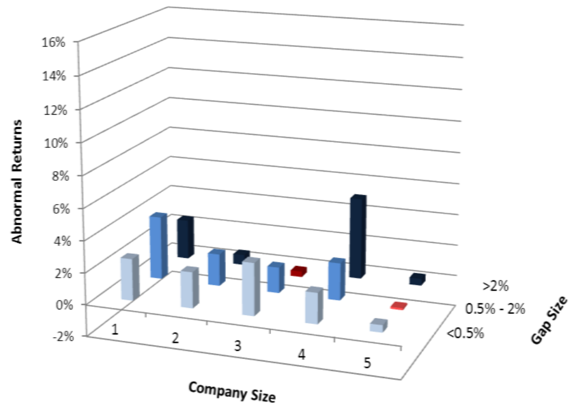
Figure C2 illustrates the abnormal returns for positive and negative gaps with 2 days holding period. The abnormal 1 month return is shown on the vertical y-axis. The company size, labeled from 1-5 (where group 1 is companies with lowest market capitalization and group 5 is companies with highest market capitalization), is shown on the horizontal x-axis. The gap size, separated in three groups, is shown on the depth axis (z-axis). Abnormal returns taking only the market factor (CAPM) into account in the risk-adjusting process, is shown to the left hand side of the figure. Abnormal returns taking both the market factor (CAPM) and the momentum factor into account in the risk-adjusting process, is shown to the right hand side of the figure. The abnormal returns are adjusted for illiquid stocks. Different shades of blue indicates positive abnormal returns while different shades of red indicates negative abnormal returns.

Figure C3. Abnormal Returns for Gaps with 3 Days Holding Period

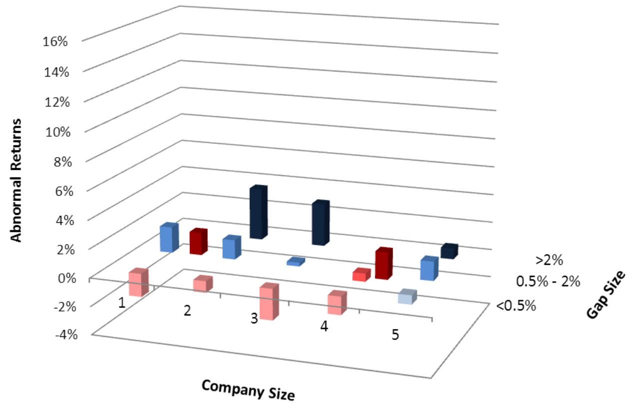
Risk-Adjusted with CAPM | Risk-Adjusted with CAPM and the Momentum Factor

Positive Gaps





Negative Gaps



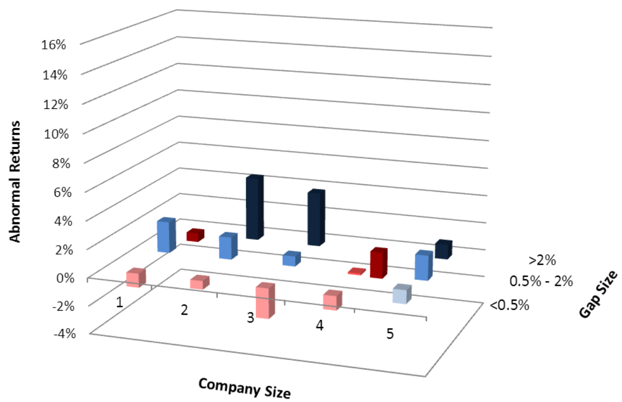


Figure C3 illustrates the abnormal returns for positive and negative gaps with 3 days holding period. The abnormal 1 month return is shown on the vertical y-axis. The company size, labeled from 1-5 (where group 1 is companies with lowest market capitalization and group 5 is companies with highest market capitalization), is shown on the horizontal x-axis. The gap size, separated in three groups, is shown on the depth axis (z-axis). Abnormal returns taking only the market factor (CAPM) into account in the risk-adjusting process, is shown to the left hand side of the figure. Abnormal returns taking both the market factor (CAPM) and the momentum factor into account in the risk-adjusting process, is shown to the right hand side of the figure. The abnormal returns are adjusted for illiquid stocks. Different shades of blue indicates positive abnormal returns while different shades of red indicates negative abnormal returns.

Figure C4. Abnormal Returns for Gaps with 4 Days Holding Period

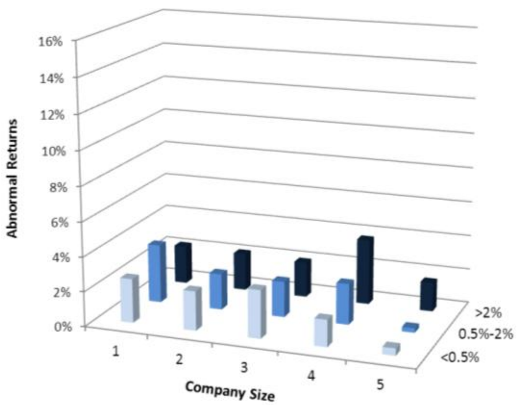
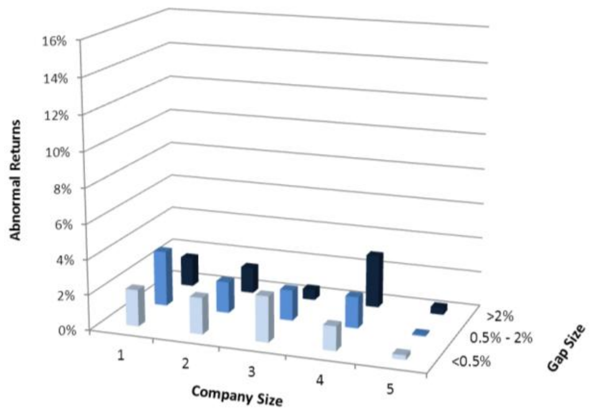
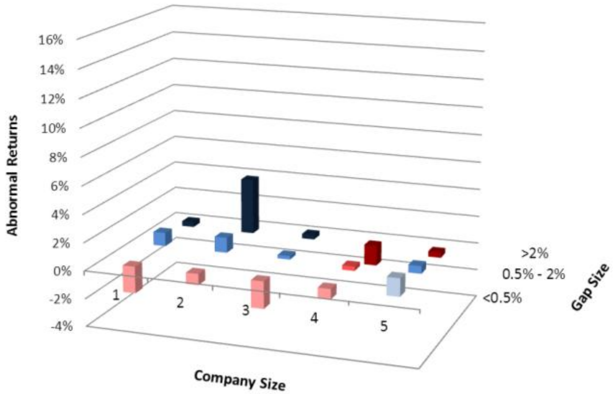
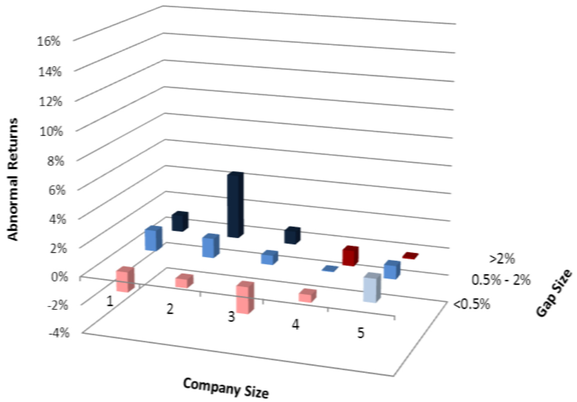
	Risk-Adjusted with CAPM	Risk-Adjusted with CAPM and the Momentum Factor
Positive Gaps		
Negative Gaps		

Figure C4 illustrates the abnormal returns for positive and negative gaps with 4 days holding period. The abnormal 1 month return is shown on the vertical y-axis. The company size, labeled from 1-5 (where group 1 is companies with lowest market capitalization and group 5 is companies with highest market capitalization), is shown on the horizontal x-axis. The gap size, separated in three groups, is shown on the depth axis (z-axis). Abnormal returns taking only the market factor (CAPM) into account in the risk-adjusting process, is shown to the left hand side of the figure. Abnormal returns taking both the market factor (CAPM) and the momentum factor into account in the risk-adjusting process, is shown to the right hand side of the figure. The abnormal returns are adjusted for illiquid stocks. Different shades of blue indicates positive abnormal returns while different shades of red indicates negative abnormal returns.

Figure C5. Abnormal Returns for Gaps with 5 Days Holding Period

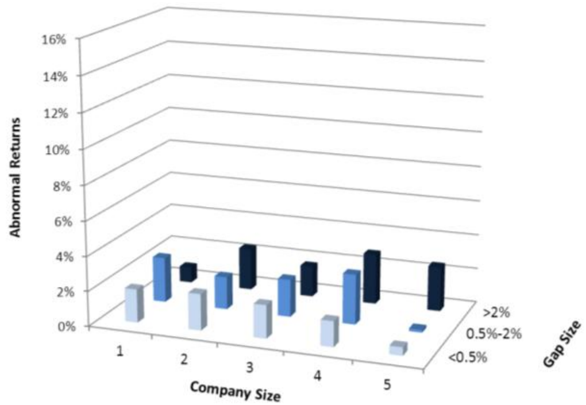
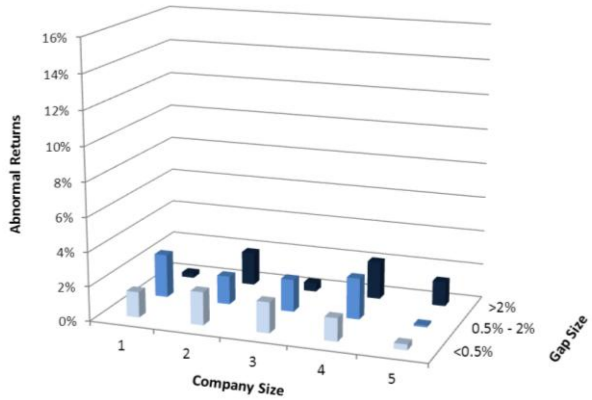
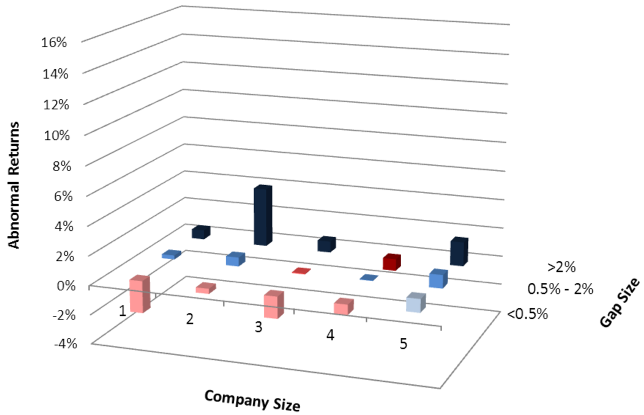
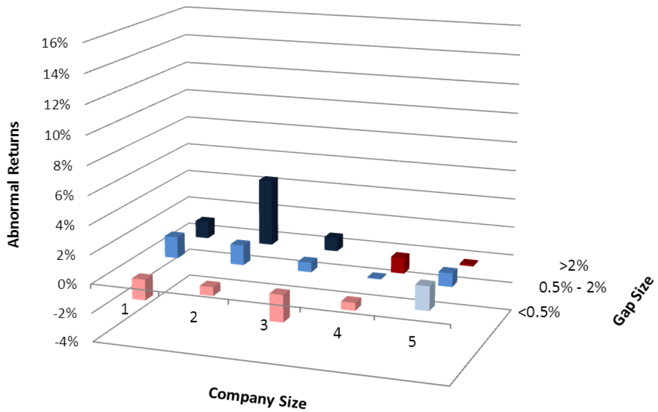
	Risk-Adjusted with CAPM	Risk-Adjusted with CAPM and the Momentum Factor
Positive Gaps		
Negative Gaps		

Figure C5 illustrates the abnormal returns for positive and negative gaps with 5 days holding period. The abnormal 1 month return is shown on the vertical y-axis. The company size, labeled from 1-5 (where group 1 is companies with lowest market capitalization and group 5 is companies with highest market capitalization), is shown on the horizontal x-axis. The gap size, separated in three groups, is shown on the depth axis (z-axis). Abnormal returns taking only the market factor (CAPM) into account in the risk-adjusting process, is shown to the left hand side of the figure. Abnormal returns taking both the market factor (CAPM) and the momentum factor into account in the risk-adjusting process, is shown to the right hand side of the figure. The abnormal returns are adjusted for illiquid stocks. Different shades of blue indicates positive abnormal returns while different shades of red indicates negative abnormal returns.

Table C1. Abnormal Returns Using CAPM

Detailed Description of Abnormal Returns Using CAPM Model

			Positive Gaps				Negative Gaps			
Holding Period	Gap Size	Company Size	Events	Mean monthly return	Adjusted returns for Trx costs	Std.dev	Events	Mean monthly return	Adjusted returns for Trx costs	Std.dev
1 Day	Small-size	Quintile 1	797	5.00%	3.75%	13.80%	790	1.15%	-0.05%	11.80%
		Quintile 2	1188	4.66%	3.42%	11.82%	1035	0.44%	-0.76%	10.95%
		Quintile 3	1398	6.48%	5.21%	10.02%	1101	3.09%	1.96%	10.56%
		Quintile 4	1425	3.92%	2.68%	9.34%	1075	1.08%	-0.12%	10.26%
		Quintile 5	1714	2.01%	0.79%	8.42%	1213	-0.30%	-1.49%	9.92%
	Mid-size	Quintile 1	2145	4.27%	3.02%	15.36%	2005	-3.47%	-4.52%	15.14%
		Quintile 2	2654	4.78%	3.54%	14.27%	2468	-2.05%	-3.18%	13.26%
		Quintile 3	2693	2.01%	0.80%	12.39%	2466	0.29%	-0.90%	12.44%
		Quintile 4	2175	6.11%	4.85%	12.24%	1942	2.23%	1.06%	13.22%
		Quintile 5	1673	1.61%	0.39%	12.66%	1397	-3.35%	-4.40%	13.59%
	Large-size	Quintile 1	859	11.79%	10.47%	29.19%	647	-2.59%	-3.69%	26.67%
		Quintile 2	1033	2.41%	1.19%	20.16%	821	-6.08%	-6.88%	21.20%
		Quintile 3	892	6.22%	4.96%	23.82%	746	-6.88%	-7.58%	23.80%
		Quintile 4	560	14.64%	13.28%	22.55%	514	1.16%	-0.03%	20.93%
		Quintile 5	403	1.43%	0.22%	17.76%	327	-1.28%	-2.44%	18.41%
2 Days	Small-size	Quintile 1	797	4.20%	3.58%	18.41%	790	1.36%	0.77%	17.72%
		Quintile 2	1188	2.46%	1.85%	16.36%	1035	0.05%	-0.54%	16.24%
		Quintile 3	1398	4.50%	3.88%	13.97%	1101	3.11%	2.58%	14.10%
		Quintile 4	1425	2.42%	1.81%	13.04%	1075	0.86%	0.26%	13.97%
		Quintile 5	1714	0.93%	0.33%	11.34%	1213	-0.43%	-1.02%	14.45%
	Mid-size	Quintile 1	2145	5.50%	4.87%	23.45%	2005	-2.45%	-2.99%	21.45%
		Quintile 2	2654	3.82%	3.20%	20.27%	2468	-1.86%	-2.42%	18.14%
		Quintile 3	2693	1.94%	1.33%	16.92%	2466	0.20%	-0.39%	17.43%
		Quintile 4	2175	4.42%	3.80%	18.43%	1942	0.62%	0.03%	18.69%
		Quintile 5	1673	2.04%	1.43%	16.97%	1397	-2.31%	-2.85%	18.90%
	Large-size	Quintile 1	859	5.41%	4.78%	37.45%	647	3.06%	2.53%	33.05%
		Quintile 2	1033	2.12%	1.51%	27.83%	821	-5.71%	-6.00%	28.94%
		Quintile 3	892	1.41%	0.81%	29.01%	746	-4.52%	-4.91%	30.26%
		Quintile 4	560	8.63%	7.99%	26.04%	514	-0.21%	-0.80%	28.56%
		Quintile 5	403	1.43%	0.82%	24.16%	327	-0.58%	-1.18%	27.08%
3 Days	Small-size	Quintile 1	797	3.08%	2.67%	20.90%	790	1.64%	1.25%	22.43%
		Quintile 2	1188	2.41%	2.01%	19.34%	1035	0.82%	0.42%	19.85%
		Quintile 3	1398	3.54%	3.13%	19.04%	1101	2.19%	1.83%	17.09%
		Quintile 4	1425	2.19%	1.78%	15.71%	1075	1.27%	0.88%	17.35%
		Quintile 5	1714	0.66%	0.25%	13.36%	1213	-0.63%	-1.02%	17.13%
	Mid-size	Quintile 1	2145	4.30%	3.89%	28.65%	2005	-1.83%	-2.19%	29.30%
		Quintile 2	2654	2.37%	1.97%	24.73%	2468	-1.38%	-1.76%	21.98%
		Quintile 3	2693	1.95%	1.55%	20.62%	2466	-0.26%	-0.66%	21.19%
		Quintile 4	2175	3.05%	2.64%	22.98%	1942	0.58%	0.18%	22.38%
		Quintile 5	1673	0.19%	-0.21%	19.89%	1397	-1.34%	-1.72%	23.10%
	Large-size	Quintile 1	859	3.19%	2.78%	44.37%	647	1.67%	1.29%	39.14%
		Quintile 2	1033	1.19%	0.79%	31.68%	821	-3.71%	-3.98%	34.84%
		Quintile 3	892	1.06%	0.66%	31.29%	746	-3.04%	-3.35%	34.49%
		Quintile 4	560	5.70%	5.29%	29.92%	514	2.01%	1.64%	32.75%
		Quintile 5	403	1.88%	1.48%	28.31%	327	-0.77%	-1.16%	30.79%
4 Days	Small-size	Quintile 1	797	2.55%	2.25%	24.33%	790	1.93%	1.65%	24.18%
		Quintile 2	1188	2.27%	1.97%	22.39%	1035	0.80%	0.51%	24.15%
		Quintile 3	1398	2.78%	2.47%	20.98%	1101	1.95%	1.67%	20.72%
		Quintile 4	1425	1.55%	1.25%	16.97%	1075	0.71%	0.41%	18.73%
		Quintile 5	1714	0.42%	0.12%	15.01%	1213	-1.27%	-1.56%	19.39%
	Mid-size	Quintile 1	2145	3.41%	3.10%	32.30%	2005	-0.98%	-1.27%	31.77%
		Quintile 2	2654	2.10%	1.80%	27.24%	2468	-1.09%	-1.38%	24.89%
		Quintile 3	2693	2.07%	1.77%	23.64%	2466	-0.25%	-0.55%	23.51%
		Quintile 4	2175	2.37%	2.07%	26.64%	1942	0.31%	0.01%	24.65%
		Quintile 5	1673	0.25%	-0.05%	22.42%	1397	-0.54%	-0.84%	24.65%
	Large-size	Quintile 1	859	2.25%	1.95%	50.00%	647	-0.37%	-0.67%	48.22%
		Quintile 2	1033	2.18%	1.88%	35.90%	821	-4.01%	-4.18%	39.68%
		Quintile 3	892	2.06%	1.76%	34.28%	746	-0.34%	-0.64%	35.67%
		Quintile 4	560	3.81%	3.50%	34.95%	514	1.47%	1.18%	42.21%
		Quintile 5	403	1.68%	1.38%	32.60%	327	0.39%	0.09%	35.13%
5 Days	Small-size	Quintile 1	797	1.92%	1.68%	26.63%	790	2.20%	2.00%	28.17%
		Quintile 2	1188	2.10%	1.85%	25.89%	1035	0.35%	0.11%	25.14%
		Quintile 3	1398	1.91%	1.67%	22.36%	1101	1.50%	1.27%	23.13%
		Quintile 4	1425	1.47%	1.22%	19.34%	1075	0.69%	0.45%	20.57%
		Quintile 5	1714	0.48%	0.24%	16.74%	1213	-0.90%	-1.14%	21.61%
	Mid-size	Quintile 1	2145	2.62%	2.37%	35.07%	2005	-0.28%	-0.52%	34.02%
		Quintile 2	2654	1.90%	1.65%	30.35%	2468	-0.62%	-0.86%	28.96%
		Quintile 3	2693	2.16%	1.92%	26.19%	2466	0.05%	-0.19%	26.18%
		Quintile 4	2175	2.88%	2.64%	29.00%	1942	-0.03%	-0.27%	27.24%
		Quintile 5	1673	0.16%	-0.08%	24.21%	1397	-0.92%	-1.15%	26.95%
	Large-size	Quintile 1	859	0.93%	0.68%	54.22%	647	-0.66%	-0.89%	51.41%
		Quintile 2	1033	2.45%	2.21%	39.36%	821	-4.06%	-4.17%	42.14%
		Quintile 3	892	1.80%	1.56%	37.37%	746	-0.78%	-1.01%	38.05%
		Quintile 4	560	2.92%	2.67%	36.07%	514	0.82%	0.59%	49.02%
		Quintile 5	403	2.59%	2.34%	35.50%	327	-1.67%	-1.89%	40.95%

Events is the number of observations of abnormal returns following gaps per category. Mean monthly return is the daily abnormal return recalculated into the monthly equivalent, assuming 20 days of trading per month. Adjusted return for Trx costs takes transactions costs into account, assuming 0.03% in transaction costs per transaction (both when buying and selling) with reference to Avanza. Std.dev shows monthly standard deviation of the abnormal returns, calculated from daily as $\text{Std.dev}_{monthly}=\text{Std.dev}_{daily} * \sqrt{20}$, assuming 20 days of trading per month. Returns on negative gaps are computed assuming short-selling after these events.

Table C2. Abnormal Returns Using CAPM and Momentum

Detailed Description of Abnormal Returns Usinng Momentum-Extended Model

			Positive Gaps				Negative Gaps			
Holding Period	**Gap Size**	**Company Size**	Events	Mean monthly return	Adjusted returns for Trx costs	Std.dev	Events	Mean monthly return	Adjusted returns for Trx costs	Std.dev
1 Day	Small-size	Quintile 1	797	4.45%	3.21%	13.62%	790	0.67%	-0.52%	11.75%
		Quintile 2	1188	4.61%	3.36%	11.80%	1035	-0.04%	-1.23%	10.78%
		Quintile 3	1398	6.09%	4.83%	10.12%	1101	3.19%	2.06%	10.45%
		Quintile 4	1425	3.64%	2.41%	9.32%	1075	0.83%	-0.37%	10.22%
		Quintile 5	1714	1.78%	0.57%	8.36%	1213	-0.46%	-1.65%	9.65%
	Mid-size	Quintile 1	2145	3.85%	2.61%	15.23%	2005	-4.04%	-5.04%	14.71%
		Quintile 2	2654	4.40%	3.16%	14.07%	2468	-2.61%	-3.71%	13.24%
		Quintile 3	2693	1.95%	0.74%	12.27%	2466	-0.29%	-1.48%	12.30%
		Quintile 4	2175	5.15%	3.90%	12.13%	1942	1.93%	0.75%	12.97%
		Quintile 5	1673	1.44%	0.23%	12.56%	1397	-3.48%	-4.52%	13.46%
	Large-size	Quintile 1	859	10.51%	9.20%	28.72%	647	-4.84%	-5.76%	26.62%
		Quintile 2	1033	1.65%	0.43%	20.04%	821	-7.65%	-8.25%	20.86%
		Quintile 3	892	5.12%	3.87%	23.40%	746	-8.02%	-8.56%	23.07%
		Quintile 4	560	14.16%	12.81%	22.59%	514	0.76%	-0.44%	19.96%
		Quintile 5	403	0.60%	-0.60%	17.34%	327	-2.97%	-4.05%	18.47%
2 Days	Small-size	Quintile 1	797	3.67%	3.05%	18.14%	790	0.70%	0.10%	17.56%
		Quintile 2	1188	2.33%	1.72%	16.23%	1035	-0.17%	-0.77%	16.01%
		Quintile 3	1398	4.18%	3.55%	13.97%	1101	3.11%	2.59%	13.98%
		Quintile 4	1425	2.14%	1.53%	12.77%	1075	0.62%	0.02%	13.78%
		Quintile 5	1714	0.75%	0.14%	11.32%	1213	-0.72%	-1.31%	13.59%
	Mid-size	Quintile 1	2145	5.15%	4.53%	23.11%	2005	-3.06%	-3.56%	21.00%
		Quintile 2	2654	3.46%	2.84%	19.82%	2468	-2.13%	-2.68%	17.95%
		Quintile 3	2693	1.68%	1.07%	16.70%	2466	-0.25%	-0.85%	17.05%
		Quintile 4	2175	3.59%	2.97%	18.14%	1942	0.30%	-0.30%	18.35%
		Quintile 5	1673	1.65%	1.05%	16.96%	1397	-2.69%	-3.21%	18.57%
	Large-size	Quintile 1	859	4.36%	3.73%	37.04%	647	1.66%	1.08%	32.72%
		Quintile 2	1033	1.62%	1.02%	27.39%	821	-6.83%	-7.00%	28.48%
		Quintile 3	892	-0.30%	-0.89%	28.09%	746	-5.92%	-6.19%	29.43%
		Quintile 4	560	8.12%	7.48%	25.65%	514	-0.13%	-0.73%	26.12%
		Quintile 5	403	0.33%	-0.27%	23.50%	327	-0.73%	-1.32%	28.21%
3 Days	Small-size	Quintile 1	797	2.63%	2.22%	20.66%	790	1.00%	0.61%	22.12%
		Quintile 2	1188	2.26%	1.85%	18.95%	1035	0.61%	0.21%	19.16%
		Quintile 3	1398	3.28%	2.87%	18.96%	1101	2.14%	1.77%	16.87%
		Quintile 4	1425	1.92%	1.52%	15.42%	1075	1.00%	0.60%	17.13%
		Quintile 5	1714	0.46%	0.06%	13.38%	1213	-0.94%	-1.33%	16.11%
	Mid-size	Quintile 1	2145	4.00%	3.59%	28.09%	2005	-2.25%	-2.60%	28.22%
		Quintile 2	2654	2.03%	1.63%	24.34%	2468	-1.61%	-1.98%	21.71%
		Quintile 3	2693	1.63%	1.23%	20.21%	2466	-0.72%	-1.12%	20.88%
		Quintile 4	2175	2.35%	1.94%	22.30%	1942	0.13%	-0.27%	22.23%
		Quintile 5	1673	-0.12%	-0.52%	20.08%	1397	-1.77%	-2.13%	22.42%
	Large-size	Quintile 1	859	2.55%	2.14%	43.71%	647	0.65%	0.25%	38.19%
		Quintile 2	1033	0.66%	0.26%	31.22%	821	-4.58%	-4.80%	34.18%
		Quintile 3	892	-0.36%	-0.76%	30.47%	746	-3.91%	-4.17%	33.62%
		Quintile 4	560	5.17%	4.76%	29.34%	514	1.94%	1.57%	31.39%
		Quintile 5	403	0.44%	0.04%	27.66%	327	-1.06%	-1.45%	32.04%
4 Days	Small-size	Quintile 1	797	2.09%	1.78%	24.01%	790	1.43%	1.15%	23.88%
		Quintile 2	1188	2.08%	1.77%	21.96%	1035	0.60%	0.30%	23.57%
		Quintile 3	1398	2.60%	2.30%	21.01%	1101	1.87%	1.60%	20.51%
		Quintile 4	1425	1.39%	1.08%	16.61%	1075	0.53%	0.23%	18.44%
		Quintile 5	1714	0.26%	-0.04%	15.02%	1213	-1.62%	-1.90%	17.85%
	Mid-size	Quintile 1	2145	3.17%	2.86%	31.42%	2005	-1.49%	-1.77%	30.51%
		Quintile 2	2654	1.80%	1.49%	26.66%	2468	-1.39%	-1.67%	24.47%
		Quintile 3	2693	1.75%	1.44%	23.09%	2466	-0.66%	-0.96%	23.10%
		Quintile 4	2175	1.79%	1.48%	25.86%	1942	-0.06%	-0.36%	24.41%
		Quintile 5	1673	0.08%	-0.22%	22.30%	1397	-0.94%	-1.23%	23.85%
	Large-size	Quintile 1	859	1.69%	1.39%	49.20%	647	-1.20%	-1.48%	46.12%
		Quintile 2	1033	1.50%	1.20%	35.45%	821	-4.62%	-4.74%	38.90%
		Quintile 3	892	0.60%	0.30%	33.46%	746	-0.95%	-1.24%	34.73%
		Quintile 4	560	3.01%	2.70%	33.72%	514	1.13%	0.83%	41.17%
		Quintile 5	403	0.39%	0.09%	32.40%	327	0.11%	-0.19%	34.52%
5 Days	Small-size	Quintile 1	797	1.49%	1.25%	26.32%	790	1.76%	1.54%	27.92%
		Quintile 2	1188	1.93%	1.69%	25.39%	1035	0.22%	-0.02%	24.62%
		Quintile 3	1398	1.79%	1.55%	22.44%	1101	1.43%	1.20%	22.70%
		Quintile 4	1425	1.34%	1.10%	18.94%	1075	0.56%	0.32%	20.07%
		Quintile 5	1714	0.33%	0.09%	16.80%	1213	-1.24%	-1.47%	19.79%
	Mid-size	Quintile 1	2145	2.53%	2.29%	34.23%	2005	-0.77%	-1.00%	32.78%
		Quintile 2	2654	1.65%	1.41%	29.71%	2468	-0.85%	-1.08%	28.28%
		Quintile 3	2693	1.89%	1.65%	25.62%	2466	-0.21%	-0.44%	25.77%
		Quintile 4	2175	2.39%	2.15%	28.21%	1942	-0.32%	-0.56%	26.90%
		Quintile 5	1673	0.11%	-0.13%	24.18%	1397	-1.35%	-1.58%	25.75%
	Large-size	Quintile 1	859	0.27%	0.03%	53.37%	647	-1.12%	-1.35%	49.54%
		Quintile 2	1033	1.96%	1.71%	38.98%	821	-4.68%	-4.75%	41.32%
		Quintile 3	892	0.50%	0.26%	36.56%	746	-1.39%	-1.62%	36.97%
		Quintile 4	560	2.19%	1.95%	34.65%	514	0.59%	0.35%	46.43%
		Quintile 5	403	1.43%	1.19%	34.90%	327	-1.38%	-1.60%	35.43%

Events is the number of observations of abnormal returns following gaps per category. Mean monthly return is the daily abnormal return recalculated into the monthly equivalent, assuming 20 days of trading per month. Adjusted return for Trx costs takes transactions costs into account, assuming 0.03% in transaction costs per transaction (both when buying and selling) with reference to Avanza. Std.dev shows monthly standard deviation of the abnormal returns, calculated from daily as $\text{Std.dev}_{\text{monthly}} = \text{Std.dev}_{\text{daily}} * \sqrt{20}$, assuming 20 days of trading per month. Returns on negative gaps are computed assuming short-selling after these events.

Appendix D: Regressions Results

Four sets of regressions have been executed for the three specified regression models in order to obtain the results below, for combinations of positive and negative gaps on the two models used. The coefficients display the impact a factor has on the abnormal returns and in which direction, either positively or negatively. Significance levels are measured by the *t*- statistic, showed below each coefficient in the different regressions. All regressions are excluding illiquid observations.

Table D1: Regression Results I

Regression I - Explanatory Power of Positive and Negative Gaps

		CAPM Model					**Momentum Extended Model**				
		Holding Period					Holding Period				
		1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days
Positive Gaps	Positive gap dummy	0.00192	0.00267	0.00264	0.00293	0.00319	0.00168	0.00216	0.00193	0.00206	0.00229
	t- statistic	*7.76*	*7.87*	*6.46*	*6.29*	*6.22*	*6.86*	*6.45*	*4.80*	*4.51*	*4.54*
	Constant	0.00027	0.00055	0.00085	0.00110	0.00135	0.00030	0.00061	0.00093	0.00121	0.00148
	t- statistic	*6.49*	*9.56*	*11.99*	*13.43*	*14.74*	*7.29*	*10.82*	*13.53*	*15.17*	*16.64*
	Number of observations	540 602	523 661	510 180	498 841	489 004	540 602	523 661	510 180	498 841	489 004
	R-squared	0.0133%	0.0140%	0.0095%	0.0090%	0.0086%	0.0105%	0.0095%	0.0053%	0.0047%	0.0047%
Negative Gaps	Negative gap dummy	0.00011	-0.00003	-0.00045	-0.00078	-0.00099	0.00036	0.00038	0.00011	-0.00009	-0.00030
	t- statistic	*0.42*	*-0.08*	*-1.01*	*-1.53*	*-1.75*	*1.39*	*1.07*	*0.25*	*-0.18*	*-0.55*
	Constant	0.00033	0.00065	0.00095	0.00122	0.00150	0.00035	0.00068	0.00100	0.00128	0.00157
	t- statistic	*8.01*	*11.20*	*13.52*	*15.01*	*16.34*	*8.45*	*11.96*	*14.49*	*16.15*	*17.69*
	Number of observations	540 602	523 661	510 180	498 841	489 004	540 602	523 661	510 180	498 841	489 004
	R-squared	0.0000%	0.0000%	0.0002%	0.0005%	0.0007%	0.0004%	0.0003%	0.0000%	0.0000%	0.0001%

Table D1 displays regression results from the specified model $AR_i = \beta_{i,0} + \beta_{i,1} * Event_i + \varepsilon_i$, run on the abnormal returns obtained from either the CAPM Model or the Momentum-Extended Model. Regressions have been run separately for holding periods of 1-5 days. ε_i is an error term. R-squared reports proportion of total sample variation of the dependent variable that is explained by the independent variables included in the model. Robust regressions have been run to correct for heteroskedasticity. Significance levels are measured by *t*-statistics, where an absolute value of the *t*-statistic above 1.64 indicates significance on the 10% level, above 1.96 on the 5% level, and above 2.54 on the 1% level. ε_i is an error term.

Table D2: Regression Results II

Regression II - Controlling for Gap Sizes

		CAPM Model					**Momentum-Extended Model**				
		Holding Period					Holding Period				
		1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days
Positive Gaps	Small-size gap	0.0018	0.0021	0.0024	0.0024	0.0023	0.0016	0.0018	0.0020	0.0019	0.0017
	t- statistic	*5.84*	*4.95*	*4.70*	*4.06*	*3.46*	*5.33*	*4.23*	*3.87*	*3.21*	*2.62*
	Mid-size gap	0.0016	0.0029	0.0028	0.0031	0.0036	0.0014	0.0024	0.0021	0.0023	0.0029
	t- statistic	*5.17*	*6.51*	*4.98*	*4.86*	*5.18*	*4.52*	*5.54*	*3.85*	*3.74*	*4.25*
	Large-size gap	0.0032	0.0030	0.0027	0.0036	0.0036	0.0027	0.0020	0.0013	0.0016	0.0014
	t- statistic	*3.31*	*2.39*	*1.85*	*2.17*	*2.03*	*2.86*	*1.60*	*0.91*	*1.01*	*0.82*
	Constant	0.0003	0.0006	0.0008	0.0011	0.0014	0.0003	0.0006	0.0009	0.0012	0.0015
	t- statistic	*6.49*	*9.56*	*11.99*	*13.43*	*14.74*	*7.29*	*10.82*	*13.53*	*15.17*	*16.64*
	Number of observations	540602	523661	510180	498841	489004	540602	523661	510180	498841	489004
	R-squared	0.015%	0.014%	0.010%	0.009%	0.009%	0.011%	0.010%	0.005%	0.005%	0.005%
Negative Gaps	Small-size gap	-0.0009	-0.0016	-0.0024	-0.0026	-0.0031	-0.0008	-0.0014	-0.0020	-0.0021	-0.0026
	t- statistic	*-2.44*	*-3.14*	*-3.84*	*-3.57*	*-3.80*	*-2.17*	*-2.74*	*-3.33*	*-3.04*	*-3.32*
	Mid-size gap	0.0002	0.0004	0.0003	-0.0002	-0.0007	0.0004	0.0008	0.0008	0.0005	0.0001
	t- statistic	*0.70*	*0.92*	*0.48*	*-0.29*	*-0.95*	*1.38*	*1.76*	*1.45*	*0.86*	*0.08*
	Large-size gap	0.0015	0.0013	0.0007	0.0006	0.0020	0.0022	0.0022	0.0017	0.0016	0.0030
	t- statistic	*1.46*	*0.97*	*0.41*	*0.29*	*0.95*	*2.15*	*1.65*	*1.03*	*0.87*	*1.44*
	Constant	0.0003	0.0006	0.0010	0.0012	0.0015	0.0003	0.0007	0.0010	0.0013	0.0016
	t- statistic	*8.01*	*11.20*	*13.52*	*15.01*	*16.34*	*8.45*	*11.96*	*14.49*	*16.15*	*17.69*
	Number of observations	540602	523661	510180	498841	489004	540602	523661	510180	498841	489004
	R-squared	0.002%	0.002%	0.002%	0.002%	0.003%	0.003%	0.003%	0.003%	0.002%	0.003%

Table D2 shows the results from the specified model $AR_i = \beta_{i,0} + \gamma_i Event_i * GapSize_{i,j} + \varepsilon_i$, where regressions have been run on the abnormal returns, for holding periods of 1-5 days, obtained either from the CAPM Model or the Momentum-Extended Model. γ_i is a set of interaction terms for Small-size gap, Mid-size gap and Large-size gap together with either Positive gap or Negative gap, for respective regression. ε_i is an error term. R-squared reports proportion of total sample variation of the dependent variable that is explained by the independent variables included in the model. Robust regressions have been run to correct for heteroskedasticity. Significance levels are measured by *t*-statistics, where an absolute value of the *t*-statistic above 1.64 indicates significance on the 10% level, above 1.96 on the 5% level, and above 2.54 on the 1% level.

Table D3: Regression Results III

Regression III - Controlling for Gap Sizes and Company Sizes											
		CAPM Model					**Momentum-Extended Model**				
		Holding Period					Holding Period				
		1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days
Positive Gaps	Small-size gap	0.0026	0.0041	0.0049	0.0045	0.0031	0.0024	0.0038	0.0045	0.0042	0.0027
	t- statistic	*3.42*	*3.88*	*3.82*	*3.11*	*1.93*	*3.15*	*3.61*	*3.60*	*2.91*	*1.71*
	Mid-size gap	0.0022	0.0046	0.0048	0.0047	0.0041	0.0020	0.0042	0.0042	0.0041	0.0035
	t- statistic	*3.12*	*4.52*	*3.81*	*3.31*	*2.58*	*2.76*	*4.10*	*3.41*	*2.95*	*2.28*
	Large-size gap	0.0038	0.0046	0.0045	0.0050	0.0040	0.0033	0.0035	0.0032	0.0032	0.0019
	t- statistic	*3.13*	*2.87*	*2.38*	*2.32*	*1.67*	*2.72*	*2.25*	*1.72*	*1.51*	*0.83*
	Size quintile 1	-0.0008	-0.0020	-0.0024	-0.0016	0.0000	-0.0007	-0.0018	-0.0023	-0.0016	0.0000
	t- statistic	*-0.90*	*-1.55*	*-1.57*	*-0.89*	*-0.02*	*-0.78*	*-1.43*	*-1.54*	*-0.92*	*-0.03*
	Size quintile 2	-0.0009	-0.0025	-0.0022	-0.0013	-0.0001	-0.0008	-0.0025	-0.0024	-0.0016	-0.0005
	t- statistic	*-1.04*	*-2.05*	*-1.53*	*-0.79*	*-0.05*	*-0.91*	*-2.10*	*-1.68*	*-0.99*	*-0.25*
	Size quintile 3	0.0003	-0.0009	-0.0011	-0.0013	0.0008	0.0002	-0.0010	-0.0013	-0.0017	0.0004
	t- statistic	*0.29*	*-0.70*	*-0.72*	*-0.78*	*0.44*	*0.24*	*-0.82*	*-0.92*	*-1.00*	*0.23*
	Size quintile 4	-0.0019	-0.0035	-0.0048	-0.0048	-0.0036	-0.0018	-0.0034	-0.0049	-0.0049	-0.0036
	t- statistic	*-2.28*	*-2.94*	*-3.35*	*-2.97*	*-2.02*	*-2.16*	*-2.93*	*-3.47*	*-3.04*	*-2.06*
	Constant	0.0003	0.0006	0.0008	0.0011	0.0014	0.0003	0.0006	0.0009	0.0012	0.0015
	t- statistic	*6.49*	*9.56*	*11.99*	*13.43*	*14.74*	*7.29*	*10.82*	*13.53*	*15.17*	*16.64*
	Number of observations	540 602	523 661	510 180	498 841	489 004	540 602	523 661	510 180	498 841	489 004
	R-squared	0.0166%	0.0171%	0.0127%	0.0117%	0.0110%	0.0132%	0.0124%	0.0088%	0.0074%	0.0070%
Negative Gaps	Small-size gap	-0.0008	-0.0015	-0.0023	-0.0025	-0.0030	-0.0007	-0.0013	-0.0020	-0.0021	-0.0025
	t- statistic	*-2.30*	*-3.01*	*-3.74*	*-3.47*	*-3.68*	*-2.05*	*-2.63*	*-3.26*	*-2.97*	*-3.24*
	Mid-size gap	0.0003	0.0005	0.0003	-0.0001	-0.0006	0.0005	0.0008	0.0009	0.0006	0.0001
	t- statistic	*0.86*	*1.06*	*0.59*	*-0.17*	*-0.82*	*1.52*	*1.88*	*1.52*	*0.94*	*0.17*
	Large-size gap	0.0016	0.0014	0.0007	0.0006	0.0021	0.0022	0.0023	0.0017	0.0017	0.0030
	t- statistic	*1.51*	*1.02*	*0.45*	*0.33*	*0.99*	*2.19*	*1.69*	*1.06*	*0.89*	*1.48*
	Size quintile 1	0.0018	0.0025	0.0023	0.0031	0.0037	0.0016	0.0021	0.0018	0.0024	0.0029
	t- statistic	*3.47*	*3.35*	*2.57*	*3.08*	*3.21*	*3.12*	*2.91*	*1.99*	*2.37*	*2.58*
	Size quintile 2	0.0017	0.0020	0.0025	0.0034	0.0036	0.0015	0.0014	0.0017	0.0024	0.0025
	t- statistic	*3.39*	*3.04*	*3.16*	*3.79*	*3.70*	*3.07*	*2.23*	*2.20*	*2.70*	*2.63*
	Size quintile 3	0.0028	0.0036	0.0037	0.0033	0.0045	0.0025	0.0029	0.0028	0.0023	0.0034
	t- statistic	*5.63*	*5.19*	*4.35*	*3.42*	*4.26*	*4.98*	*4.35*	*3.44*	*2.48*	*3.34*
	Size quintile 4	0.0006	0.0009	0.0000	-0.0002	0.0000	0.0005	0.0005	-0.0007	-0.0008	-0.0007
	t- statistic	*1.32*	*1.43*	*-0.05*	*-0.26*	*-0.05*	*1.01*	*0.78*	*-0.91*	*-1.04*	*-0.74*
	Constant	0.0003	0.0006	0.0009	0.0012	0.0014	0.0003	0.0006	0.0010	0.0012	0.0015
	t- statistic	*6.70*	*9.92*	*12.43*	*13.89*	*15.11*	*7.26*	*10.90*	*13.67*	*15.30*	*16.71*
	Number of observations	540 602	523 661	510 180	498 841	489 004	540 602	523 661	510 180	498 841	489 004
	R-squared	0.0127%	0.0115%	0.0092%	0.0091%	0.0111%	0.0120%	0.0095%	0.0068%	0.0060%	0.0078%

Table D3 shows the regression results from the CAPM Model and the Momentum-Extended Model for the specified model $AR_i = \beta_{i,0} + \gamma_{i,1} Event_i * GapSize_{i,j} + \gamma_{i,2} * Event_i * CompanySize_{i,k} + \varepsilon_i$. Regressions have been run separately for holding periods of 1-5 days. $\gamma_{i,1}$ is a set of interaction terms for Small-size gap, Mid-size gap and Large-size gap together with either Positive gap or Negative gap, for respective regression. $\gamma_{i,2}$ is similarly a set of interaction terms for Company size together with Positive or Negative gap. ε_i is an error term. In order to avoid the dummy variable trap of perfect collinearity, size quintile 5 is chosen as the benchmark group against which comparisons are made. R-squared reports proportion of total sample variation of the dependent variable that is explained by the independent variables included in the model. Robust regressions have been run to correct for heteroskedasticity. Significance levels are measured by *t*-statistics, where an absolute value of the *t*-statistic above 1.64 indicates significance on the 10% level, above 1.96 on the 5% level, and above 2.54 on the 1% level.

APPENDIX E: LIST OF INCLUDED STOCKS

Table E1: Companies Included in the Dataset

Included Companies in the Dataset, A-Li		
AarhusKarlshamn AB	Carl Lamm AB	Hakon Invest AB
AB Sagax	Carnegie & Co AB, D.	Haldex AB
ABB Ltd	Cash Guard AB ser. B	Havsfrun Investment, AB ser. B
AcadeMedia AB ser. B	Castellum AB	Heba Fastighets AB ser. B
Acando AB, ser. B	Catella AB ser. A	Hemtex AB
ACAP Invest AB ser. B	Catella AB ser. B	Hennes & Mauritz AB, H & M ser. B
A-Com AB	Catena AB	Hexagon AB ser. B
Active Biotech AB	CellaVision AB	HEXPOL AB, ser. B
AddNode AB ser. B	Cision AB	HiQ International AB
Addtech AB ser. B	Clas Ohlson AB ser. B	HL Display AB ser. B
Aerocrine AB, ser. B	Cloetta AB ser. B	HMS Networks AB
Affärsstrategerna AB ser. B	Coastal Contacts Inc.	Holmen AB ser. B
Alfa Laval AB	Concordia Maritime AB ser. B	Home Properties AB
All Cards Service Center - ACSC AB	Connecta AB	HQ AB
Allenex AB	Consilium AB ser. B	HQ Fonder AB
Alliance Oil Company Ltd	Corem Property Group	Hufvudstaden AB ser. A
AllTele Allmänna Svenska Telefon AB	CTT Systems AB	HUMAN CARE H C AB
Anoto Group AB	Cybercom Group AB	Husqvarna AB, ser. B
Artimplant AB ser. B	Dagon AB	Höganäs AB ser. B
Aspiro AB	DGC One AB	I.A.R Systems AB (Gamla)
ASSA ABLOY AB ser. B	Diamyd Medical AB ser. B	I.A.R Systems Group AB ser. B
AstraZeneca PLC	Diös AB	Image Systema AB
Atlas Copco AB ser. A	DORO AB	Industrial and Financial Syst. AB ser. B
Atrium Ljungberg AB ser. B	Duni AB	Industrivärden, AB ser. A
AudioDev AB ser B	Duroc AB ser. B	Indutrade AB
Autoliv Inc. SDB	East Capital Explorer AB	Intellecta AB ser. B
Avanza AB	Elanders AB ser. B	Intentia International AB ser. B
Avega Group AB	Electra Gruppen AB	Intrum Justitia AB
Axfood AB	Electrolux, AB ser. B	Investment AB Kinnevik, ser. A
Axis AB	Elekta AB ser. B	Investment AB Kinnevik, ser. B
B&B TOOLS AB ser. B	ElektronikGruppen BK AB ser. B	Investor AB ser. A
Ballingslöv International AB	Elos AB ser. B	Investor AB ser. B
BE Group AB	Enea AB	Invik & Co AB ser. B
Beijer AB, G & L ser. B	Eniro AB	ITAB Shop Concept ser. B
Beijer Alma AB ser. B	EpiCept Corporation	JC AB
Beijer Electronics AB	Ericsson, ser. B	Jeeves Information Systems AB
Bergs Timber AB, ser. B	eWork Scandinavia AB	JM AB
Betsson AB ser. B	Fabege AB	KABE AB ser. B
Bilia AB ser. A	Fabege AB ser. B	KappAhl AB
Billerud AB	Fagerhult, AB	Karlshamns AB
BioGaia AB ser. B	Fast Partner AB	Karo Bio AB
BioInvent International AB	Fastighets AB Balder, ser. B	Kaupþing Bank hf.
Biolin Scientific AB	Fazer Konfektyr Service AB ser. B	Kinnevik, Industriförvaltnings AB ser. B
BioPhausia AB	Feelgood Svenska AB	KLIPPAN AB
Biotage AB	Fenix Outdoor AB ser. B	Klövern AB
Björn Borg AB	Fingerprint Cards AB ser. B	Klövern AB ser. A
Black Earth Farming Ltd SDB	Finnveden TIAB	Know IT AB
Boliden AB	Formpipe Software AB	Kungsleden AB
Bong Ljungdahl AB	Gambro AB ser. A	Lagercrantz Group AB ser B
Borås Wäfveri AB ser. B	Gant Company AB	Lammhults Design Group AB ser. B
Boss Media AB	Getinge AB ser. B	Latour, Investmentab. ser. B
Brinova Fastigheter AB ser.B	Geveko, AB ser. B	Lawson Software Inc
Broström AB ser.B	Global Health Partner AB	LB Icon AB
BTS Group AB ser. B	Glocalnet AB	LBI International AB
Bure Equity AB	Gorthon Lines AB ser. B	Ledstiernan AB ser. B
Capio TIA	Gunnebo AB	Lindab International AB
Cardo AB	Gunnebo Industrier AB	Lindex TIA

Included Companies in the Dataset, Lo-Ö

Loomis AB ser. B	Orc Group AB	SkiStar AB ser. B
Lundbergföretagen AB, L E ser. B	Orexo AB	Softronic AB ser. B
Lundin Mining Corporation	Oriflame Cosmetics S.A, SDB	Song Networks Holding AB
Lundin Petroleum AB	Ortivus AB ser. B	SSAB AB ser. A
Luxonen S.A. SDB	Oxigene, Inc.	StjärnaFyrkant AB
Malmbergs Elektriska AB ser. B	PA Resources AB	Stora Enso Oyj ser. R
Mandator AB	PartnerTech AB	Strålfors B
Maxim Pharmaceuticals, Inc.	Peab AB ser. B	Studsvik AB
Meda AB ser. A	Peab Industri AB, ser. B	SWECO AB ser. B
MEDICOVER Holding S.A SDB	Pfizer Inc.	Swedbank AB ser. A
Medivir AB ser. B	Pharmacia Corporation SDB	Svedbergs i Dalstorp AB ser. B
Mekonomen AB	Phonera AB	Swedish Match AB
Melker Schörling AB	Poolia AB ser. B	Swedish Oprhan Biovitrum AB
Metro International S.A SDB ser. A	Powerwave Technologies Inc	Swedol AB, ser. B
Metro International S.A SDB ser. B	Precise Biometrics AB	Svenska Cellulosa AB SCA ser. B
Micronic Mydata AB	Prevas AB ser. B	Svenska Handelsbanken ser. A
Midsona AB ser. B	Pricer AB ser. B	Svithoid Tankers AB, ser. B
Midway Holding AB ser. B	Proact IT Group AB	Svolder AB ser. B
Millicom International Cellular S.A. SDB	Probi AB	Systemair AB
Modern Times Group MTG AB ser. B	Proffice AB ser. B	SäkI AB
Modul 1 Data AB	ProfilGruppen AB ser. B	Tanganyika Oil Company Ltd. SDB
Morphic Technologies B	Protect Data AB	Tele2 AB ser. B
MSC Konsult AB ser. B	PSI Group ASA	Teleca AB ser. B
MultiQ International AB	Q-Med AB	Telelogic AB
Munters AB	Ratos AB ser. A	TeliaSonera AB
NAXS Nordic Access Buyout Fund	Ratos AB ser. B	Teligent AB
NCC AB ser. A	RaySearch Laboratories AB ser. B	Ticket Travel Group AB
NCC AB ser. B	ReadSoft AB ser. B	Tieto Abp
Nederman Holding AB	Rederi AB Transatlantic, ser. B	Tivox AB ser. B
Nefab AB ser. B	Rejlerkoncernen AB, ser. B	Traction AB ser. B
Neonet AB	Resco AB ser. B	TradeDoubler AB
Net Entertainment NE AB ser. B	Rezidor Hotel Group AB	Transcom WorldWide S.A SDB ser. A
Net Insight AB ser. B	Riddarhyttan Resources AB	Transcom WorldWide S.A SDB ser. B
Netonnet AB	rnb Retail and Brands AB	Trelleborg AB ser. B
New Wave Group AB ser. B	Rottneros AB	Tricorona AB
NIBE Industrier AB ser. B	Rörvik Timber AB ser. B	Trigon Agri A/S
Nilörngruppen AB ser. B	SAAB AB ser. B	Trio AB
Niscayah Group AB, ser. B	SalusAnsvar AB TIA ser. B	TurnIT AB ser. B
Nobel Biocare Holding AG	Sandvik AB	Unibet Group Plc, SDB
Nobia AB	Sapa AB	Uniflex AB, ser. B
Nokia Oyj, SEK	Sardus, AB	Wallenstam AB, ser. B
Nolato AB ser. B	SAS AB	VBG Group AB ser. B
Nordea Bank AB	SCANIA AB ser. B	Venue Retail Group AB ser. B
Nordic Mines AB	ScanMining AB	Wihlborgs Fatigheter AB
Nordic Serv Part Hldg AB, ser. B	Seco Tools AB ser. B	Vitrolife AB
Nordnet AB ser. B	SECTRA AB ser B	Volvo, AB ser. B
Norsk Hydro ASA SDB	Securitas AB ser. B	Vostok Gas Ltd SDB
NOTE AB	Securitas Direct AB, ser. B	Vostok Nafta Investment Ltd, SDB
NovaCast Technologies AB, ser. B	Semcon AB	XANO Industri AB ser. B
Novestra, AB	Sensys Traffic AB	XponCard Group AB
NOVOTEK AB ser. B	Sigma AB ser. B	Zodiak Television AB ser. B
Oasmia Pharmaceutical AB	SinterCast AB	ÅF AB ser. B
Odd Molly International AB	Skandia	Öresund, Investmentab
OEM International AB ser. B	Skandinaviska Enskilda Banken ser. A	
Old Mutual Plc	Skanditek Industriförvaltning AB.	
Opcon AB	Skanska AB ser. B	
Optimail AB ser. A	SKF, AB ser. B	