INTRADAY PRICE REVERSALS AND MOMENTUM: EVIDENCE FROM THE NYSE

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ABSTRACT

This study looks at intraday momentum and reversal returns by using an innovative threshold methodology instead of a traditional relative peer ranking methodology. In contrast to longer time windows, this study shows that momentum still exists for NYSE listed stocks between 2000 and 2015 for the intraday sphere yielding a maximum return of 0.2% per day which drops when looking at later time periods. The returns found are too low to cover all transaction costs, therefore, the intraday momentum returns found are not economically significant. In addition to the momentum anomaly, the dataset is also used to test for possible reversal effects. Reversals found yield a maximum daily return of 3.29%2. The reversal return is highly economical significant and is more than sufficient to cover all transaction costs. Evidence furthermore shows that intraday momentum crashes after a period of recession and reversal returns flourish; which is consistent with previous momentum literature based on longer time windows.

During the 1970's the Efficient Market Hypothesis (Burton and Fama, 1970) flourished among both academics and investors because it represented the theoretical trends at the time very well. The hypothesis entails that the price of an asset always incorporates and reflects all relevant available information and prices only shift due to new qualitative information arriving to the market. This suggests that assets are correctly priced and markets are not likely to offer abnormal returns that are in any way justified by underlying fundamentals. From the moment that Burton and Fama (1970) prosed the Efficient Market Hypothesis it was evident that it did not cover all possible market movements. Literature lacked concrete evidence rebutting the Efficient Market Hypothesis at the time and thus there was a strong believe among certain investors in the Efficient Market Hypothesis which made the buy and hold strategy the prevailing investment strategy at the time.

During the 1980's more robust evidence for asset pricing anomalies appeared (e.g. the January-effect and the September-effect) that undermined the Efficient Market Hypothesis[1]. Anomalies in assets pricing indicated that returns were not a 'random walk' like the Efficient Market

[1] For a more comprehensive overview of anomalies see Siegel (2002).

Hypothesis prescribed. This gave investors the opportunity to exploit different sorts of asset pricing anomalies - the 1980's can therefore be seen as the origin of the quantitative trading era we are now experiencing where an increasing number of trades are made by highly automated algorithms trying to exploit anomalies[2].

In this study, we will continue to build upon one of the most known and exploited approaches to benefit from asset pricing anomalies: the "loser/winner ranking". The broadly investigated, and applied, contrarian and momentum strategies are derived from the loser/winner ranking (Grinblatt and Titman, 1989, 1993). The loser/winner approach ranks the given assets based on their returns in the previous period (or formation period). A contrarian trader is under the impression that the market is experiencing an overreaction to the available market information and therefore forecasts that the market will correct itself in a subsequent period (also referred to as the holding period). In his effort to profit from the overreaction, the contrarian trader will sell short the top performers (winners) and buy the worst performers (losers) based on the ranking of the formation period. In sharp contrast, a momentum trader is under the impression that the market experiences an under reaction to the available market information. In effort to profit from the under reaction the momentum trader buys the winners and sells the losers. The contrarian and momentum strategies come in many flavors as to the length of the formation and holding period and the classification of winners and losers (e.g. using top deciles or quartiles as winners). There is plentiful research and evidence in literature around momentum and contrarian profitability but, since there are many variants possible, literature is somewhat scattered and occasionally finds contrary evidence.

De Bondt and Thaler (1985, 1987) were among the first to provide concrete evidence for the contrarian anomaly and show that past losers will outperform past winners in the subsequent period; providing proof that the contrarian strategy yields a significant positive return for a four-year period. The first study to provide evidence of a momentum anomaly was by Jegadeesh and Titman (1993); finding a market under reaction that can be exploited by the momentum strategy which would yield a yearly excess return of 12.01%. Perhaps the most fascinating about this high excess return is that the Sharpe ratio of the momentum strategy exceeded the Sharpe ratio of the market itself, as well as the value and size factors. After these

[2] For a comprehensive, yearly, NYSE traded volume overview see: http://www.nyxdata.com/nysedata/asp/factbook/viewer_edition.asp?mode=table&key=268&category=14

first studies, many followed examining the contrarian and momentum strategy in different markets and with different setups[3].

Literature trying to explain the rationale behind the profitability of momentum and contrarian strategies can be divided into two categories; behavioral finance and rational-risk-based models. Traditional literature could no longer justify the newly found asset pricing anomalies, this eventually led to the rise of a new field in economic literature in the 1990's: financial behavior – combing financial markets with human psychology. Financial behavior literature presents several explanations for the asset pricing anomalies found using the momentum and contrarian strategies. In their first study Jegadeesh and Titman (1993) already attributed their results to a cognitive expectation bias which would lead to investors having excessive expectations about winners and losers. They show that winners provide consistently higher returns around their earnings announcement. However, in the 13-month period following the earning announcement losers outperform past winners which indicates that there is a cognitive expectation bias in play. In addition, the authors find that investors experience an under-reaction bias to firm or industry specific news which smooths out the price effect of news which leads to momentum returns. Daniel et al. (1998) theorize that an investor overestimates his own ability to understand the significance of existing information, and on top of that, overestimates his ability to generate new information. Daniel et al. (1998) classify this as a self-attribution bias. The authors conclude that investors underreact to public information and overreact to private information. In addition, investors applying the momentum strategy are also contributing themselves to the asset pricing anomaly since they are never the first responders to new market information and respond purely on market movements. The momentum strategy is therefore in a way a self-fulfilling prophecy.

New market information, and more specifically how information is processed by investors, is key to understanding the cognitive bias errors in asset pricing. Hong et al. (2000) try to capture the cognitive bias and possible information effects on momentum by looking how different investors react to new market information. A proxy based on the level of analyst coverage is

[3] E.g. see Asness et al. (1997) and Chan et al. (2000) for country indices, Rouwenhorst (1998) and Asness et al. (2013) for international evidence, Moskowitz and Grinblatt (1999) and Swinkels (2002) for industry portfolios, Liu and Lee (2001) for the Japanese stock market, Menkhoff et al. (2012) for currency markets, Erb and Harvey (2015) for commodities, Bernard and Deo (2015) for Indian stock markets, Daniel and Moskowitz (2016) for momentum during recessions and Narayan and Phan (2017) for Islamic stock momentum.

used to capture new market information while in the meantime correcting for the size heuristic which links the level of analyst coverage to firm size (Bhushan, 1989). The results indicate that a firm with low analyst coverage has more momentum due to a slow information flow; smoothening out the shift in asset pricing over a longer period which leads to a stronger serial correlation (i.e. momentum). A cognitive bias can be observed by looking at the momentum returns for low coverage firms. Low coverage winners seem to yield no momentum returns while low coverage losers seem to yield high momentum returns. This makes intuitive sense in the way that a low coverage firm sitting on good news wants to get this news out to the market and thus increases their disclosures or gives out an official statement. On the other hand, a low coverage firm sitting on bad news is not inclined to give out statements or disclosures to communicate this bad news to the market and leaves this task open for the analysts. However, since these are firms with a low coverage level the news gets out rather slowly with the effect that investors respond immediately to good news which originates from the firms themselves, indicating a cognitive bias in the form of a confirmation bias, and slowly to bad news which arrives to the market through analysts. Note, however, that Hong et al. (2000) use three portfolios to capture momentum effects, instead of the broadly accepted decile method, this could indicate a flaw in their methodology of deriving the momentum returns.

Next to behavioral evidence for asset pricing anomalies, there is a second category of studies that focuses on rational-risk-based models. These studies focus on finding determinants that explain prominent anomalies. The well-known three-factor model (Fama and French, 1992, 1993) cannot explain all asset pricing anomalies found, although some of their factors contribute significantly. The first, and most straightforward determinant, is firm size (also included in the three-factor model), which is documented in multiple studies (e.g. Jegadeesh and Titman (1993), Hong et al. (2000) and Grinblatt and Moskowitz (2004)), of which Schmidt et al. (2015) provide the most extensive evidence. Working with 23 stock markets globally, the authors find that momentum profitability drops significantly with firm size. The most common rationale for the size determinant is that smaller firms are more volatile which in turn leads to better momentum returns (although behavioral finance argues it is due to a sluggish information flow). Avramov et al. (2016) provide evidence that momentum is also correlated with the determinant stock liquidity. The authors argue that liquid markets know a higher momentum anomaly. Their evidence points out that illiquidity negatively correlates with investor overconfidence which in turn positively affects momentum. The authors conclude that liquidity is therefore a useful predictor of momentum returns. But perhaps the underlying instigator to market illiquidity is the state of the real economy; which is also suggested by Næs et al. (2011). Macroeconomists argue that the stock market is simply a lagged indicator of macroeconomic circumstances and therefore rationalize that macroeconomic determinants should explain return variances. This is consistent with findings by Chen et al. (1986). Moskowitz and Grinblatt (1999) look at macroeconomic determinants and industry factors and more specifically how they affect momentum returns. Moskowitz and Grinblatt (1999) conclude that momentum returns are mainly driven by industry factors. Griffin et al. (2003) expand the research done by Moskowitz and Grinblatt (1999) and tests globally if there is a relationship between macroeconomic factors and momentum returns and hope to get a better understanding of specific macroeconomic determinants. Using data of 40 countries Griffin et al. (2003) conclude that momentum profits cannot be explained by macroeconomic factors.

Seasonality also seems to play a role in momentum returns. Jegadeesh and Titman (1993) already stumbled across, and highlighted, the January effect. Jegadeesh and Titman (1993, 2001) and Grundy and Martin (2001) indicate that past winners will outperform past losers for every month except for January; indicating a seasonality effect. The momentum strategy will lose as much as 7% for the month January and this is predominantly caused by small-cap stocks (Jegadeesh and Titman, 1993). The widely accepted explanation for the January-effect is based around tax-loss selling of stocks that have underperformed in the current year and thus are sold by investors in December and will bounce back in January; disturbing the momentum strategy returns.

Apart from the enormous amount of literature examining the momentum and contrarian anomaly and the associated underlying explanations, there is also extensive evidence indicating that using the momentum strategy comes at huge costs when markets experience significant downturns; making it less appealing to investors who are risk averse and dislike kurtosis and negative skewness. In 1932 the momentum strategy returned -91.59% in just two months and in 2009 -73.42% in just three months; demonstrating the large impact that momentum strategy could have if left unhedged (Barroso and Santa-Clara, 2015). Literature shows that momentum crashes right after an economic downturn. This can be explained by the fact that low beta stocks perform relatively well during a market downturn and will thus be selected as winners in the formation period. When markets eventually recover the high beta stocks will outperform the low beta stocks leading the momentum portfolio to crash right after an economic downturn (Daniel and Moskowitz, 2016).

As with all arbitrage/anomaly opportunities, anomalies are traded away over time or eventually become so small that only investors with the lowest possible trading costs can proof to be profitable utilizing it (Chordia et al. 2014). The fact that the momentum strategy has proven itself highly vulnerable to crashes, new technological developments and the fact that longer momentum time windows became unprofitable (Schulmeister 2009) has pushed the momentum strategy to shorter time windows. The shorter (intraday) time window will make momentum less tangible for system wide crashes and even makes it possible to profit from crashes as these are characterized by high volatility periods. Among existing literature there is a relative paucity of studies looking at intraday time series momentum profitability, although the market is clearly trending toward more quantitative short-term trading. This study will therefore investigate whether or not momentum still exists for 2,732 NYSE listed firms between 2000 and 2015 based on an intraday time window. Reasons behind the small number of intraday studies may be that ultra-short intraday periods yield low returns or that it is due to a lack of intraday data availability. Inspired by the methodology used in Holmberg et al. (2013) this study will tackle the latter problem using an innovative solution to test intraday strategies without using intraday data. This study will use existing momentum theory and traditional momentum methodology as foundation but will make one key modification; traditional methodology uses a relative peer ranking to pick winners and losers which makes individual stocks dependent on other stocks and thus cancels out 80% of eligible stocks (decile two to nine) based on characteritics of the peer group. It is our believe that each stock should be considered independent from where they are ranked in a distribution. Therefore, we will consider each individual stock in our methodology using Opening Range Breakout thresholds.

This study finds that momentum still exists for 2,732 NYSE listed stocks between 2000 and 2015 in the intraday sphere with a maximum return of 0.2% per day which drops when looking at later periods. Unfortunately, this return is too low to cover all costs, i.e. the bid-ask spread, transaction costs and possible trades with insufficient volumes to fill the complete order which are additional costs as well. The momentum returns found in this study are therefore not economically significant. In addition to the momentum returns the dataset is also used to test for reversal returns. Reversals are found to yield a maximum return of 3.29% a day which is highly economical significant and is more than sufficient to cover all transaction costs. Evidence furthermore indicates that intraday momentum crashes right after a period of recession and reversals flourishes which is consistent with findings by Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016).

I. RELATED INTRADAY LITERATURE

The asset pricing anomalies found in the 1980's gave investors not only the opportunity to make investment strategies around it but also gave investors a first real taste of quantitative trading strategies. The momentum and contrarian strategies could now be implemented using an automated system that picked the stocks based on a simple algorithm. As a result of improving technologies and increasing research, algorithms are now at a point where they are responsible for more than half of the daily volume. As algorithms slowly gained traction they moved from long time windows to shorter time windows where we are now at a point that they can operate intraday or even on time frames of milliseconds[4]. The explanation for this shift is that longer time window algorithms have been steadily losing their profitability from the 1960s to the 1990s; in which they eventually became unprofitable. However, when examining the exact same models on a shorter 30-minute window Schulmeister (2009) finds that the same algorithms still work for higher frequencies as it produces an average gross return of 8.8% per year using the S&P500 spot and futures market for the years 1983 to 2000. Not only the S&P500 futures and spot market have proven to be more efficient nowadays as literature points

[4] The term intraday trading was first introduced by Crabel (1990) in his book "Day trading with short term price patterns and opening range breakout".

out that many more markets can no longer be profitably exploited by technical trading rules[5]. The reason that markets nowadays are more efficient seems to be a result of the increasingly lower transaction costs, lower computer cost and increased liquidity. Some argue that the unprofitability of these technical trading strategies for longer time windows is just a temporal phenomenon that will eventually fade out and technical trading rules will become profitable again in the future. However, after a decade of even more efficient markets, also caused by the ever-improving information technologies that have increased market efficiency even further, we can now say with confidence that this argument is incorrect.

Since the short term, intraday, strategies still proof to be profitable that is where this study will be focusing on. Intraday strategies can be divided into multiple categories, this study will investigate two: reversal strategies and momentum strategies (also called relative strength strategies). Reversal strategies are built on the idea that a prior price movement, intraday or overnight, will eventually revert itself. Working with Hong Kong index futures Fung and Lam (2004) observe intraday price reversals mainly at the opening of the market if there was a large overnight price adjustment up or down the night before. In an earlier study Fung et al. (2000) already provided proof that the magnitude of the price reversal is associated with the initial price change. Fung and Lam (2004) attribute the reversal to an overreaction bias that happened overnight and which is corrected in the morning. After the first hours of trading the index futures will catch up and convert back to their fair pricing. Fung and Lam (2004) record the same reversal effects during the day but these are less robust. On top of that, tracking the price reversal for multiple days shows signs of autocorrelations extending beyond intraday to the following day. For NYSE listed stocks a comparable negative correlation between overnight returns and intraday returns is found experiencing the strongest reversal effects in the morning (Stoll and Whaley, 1990). To test whether or not reversals happen in the morning or in the afternoon it is interesting to look at a market that doesn’t trade continuously throughout the day but halts trading for lunch purposes. Amihud and Mendelson (1991) therefore look at the Japanese stock market since this is a market with two openings during the day which provides them with a perfect dataset to test for intraday differences. Their results indicate that on the

[5] E.g. Sullivan et al. (1999) for stock markets (DJIA), Olson (2004), Schulmeister (2007A), Schulmeister (2007B) and Frömmel and Lampaert (2016) for exchange markets and Irwin and Park (2005) for multiple future markets.

Japanese stock market there is a negative correlation between overnight returns and daytime returns which is larger during the trading session in the morning (i.e. a reversal effect occurs which is consistent with the findings of Stoll and Whaley (1990) and Fung and Lam (2004)). The authors also find that a Japanese trading day is most volatile in the first period of the day (open-to-open) compared to the second period of the day (close-to-close). The magnitude of intraday price reversals varies among industries and firms. However, theory prescribes that there should be a larger reversal effect for small stocks that experience a below average liquidity. The rationale for this is that smaller stocks generate less attention and have a smaller shareholders base to process new information and therefore take a longer period of time to achieve efficient pricing. Indeed, Verousis and Ap Gwilym (2011) find that reversals are more prevalent for smaller stocks and when trade sizes are smaller.

The study by Kang (2005) shows that intraday return patterns for small and large stocks are significantly different from each other. Based on hourly returns for two thousand stocks listed on the NYSE Kang (2005) divides his sample into a small stock and large stock sub-sample to test for significant intraday return differences. Based on the original momentum theory, set out by Jegadeesh and Titman (1993), Kang (2005) sorts stocks in the sub-samples by a loser/winner ranking and analyzes their momentum performance using mid-quote prices (average between lowest ask and highest bid). The results indicate that there is a significant intraday return difference between large cap stocks and small cap stocks. The large stock sub-sample for one and a half hour displays a momentum heuristic, meaning that past winners will keep outperforming past losers in the subsequent period. After the one and a half hour period a reversal effect kicks in; leading the momentum returns to crash as winners will start underperforming past losers for the rest of the day. The small stock sub-sample, however, behaves differently and does not experience a momentum-reversal but a continued momentum for the whole trading day. Additionally, the author concludes that the momentum effect is stronger in the morning than in the afternoon which is consistent with previous findings in reversal literature that a reversal effect is strongest in the morning. Kang (2005) suggests that the incorporation of information in the morning could take longer due to a larger amount of information that needs to be processed by the market. The strong reversal effect in the morning could be the heuristic fueling the momentum anomaly found by Kang (2005). This would be in line with Bysshe (2004) who in his book "Trading the 10 O'clock Bulls" claims that 35% of the trading days the day high and day low are set during the opening and that if a stock breaks out of his opening range it is highly probable that the stock will show a continuation in the direction of the break out which we would classify as momentum. Suggested explanations for the large-cap/small-cap difference are liquidity-driven mechanisms or an initial under reaction. Another suggested explanation is that large stocks have a better processing speed due to a larger investor base and higher liquidity which is also found in previous literature (e.g. Lo and MacKinlay, 1990). In contrast to our study, Kang (2005) uses a portfolio level methodology to calculate momentum returns rather than testing momentum returns based on individual stocks.

The study performed by Venter (2009) comes close to this study as it is one of few studies that closely documents both intraday momentum and contrarian returns. Using JSE (Johannesburg Stock Exchange) data Venter (2009) ends up with 144 eligible stocks for the year 2007. Similar to Kang (2005), Venter (2009) uses the loser/winner ranking methodology and mid-quote prices to avoid possible bid-ask spread bounces. The methodology used works with formation periods ranging from one hour to two and a half hour using half hour intervals and uses holding periods that range from one to five hours with hourly intervals. The author assumes there are no transaction costs and that there is always enough volume at the best bid and ask prices. Especially the latter is an optimistic assumption as it is very unlikely that there is always enough volume to fill the complete order. If there is not enough volume it would cause the investor to move further out to the second or third best price which would obviously have a negative effect on the returns measured. Findings indicate that significant momentum effects were not present but reversal effects were to some extent. However, replacing the mid-quote pricing by the best bid-ask pricing assumptions, that are more realistic, reveals that these effects are too small to be profitably implemented. The author further shows that reversals are strongest for small cap stock both on the extreme losers and winners side and contrarian effects are mainly caused by small cap stocks.

In this study, we will be using Opening Range Breakouts (ORB) to test for profitability of breakouts based on a momentum strategy. The only study, to the best of the authors knowledge, using the same methodology with the same purpose is Holmberg et al. (2013) who, like this study, only use the Open, High, Low, and Close data to test for intraday asset pricing anomalies. The Opening Range Breakout strategy is based on the momentum strategy that if a stock price moves beyond a certain level the chances are that it will continue a move in that direction. The Opening Range Breakout filter sets a certain threshold above and below the opening or closing price and closely follows the price pattern; if either one of the thresholds is passed a position in the stock is taken. The Opening Range Breakout filter is therefore actually a long volatility play. Although Wang and Xu (2015) argue that momentum crashes when it endures high volatility for longer time windows, we hope to find the opposite. Namely, that momentum prospers during high intraday volatility using our methodology. The main difference using the Opening Range Breakout filter compared to the traditional momentum strategy is that the Opening Range Breakout filter is based on individual stocks showing a certain amount of strength, or weakness, during the intraday trading session. Whereas momentum also looks for strength and weaknesses but does this by means of a portfolio of stocks based on a relative peer distribution. Holmberg et al. (2013) use U.S. crude oil futures data for the years 1983 to 2011. To assess the significance of the found returns the authors use a bootstrap approach which is based on the methodology used by Brock et al. (1992). The authors find that using upper and lower thresholds is highly profitable. However, when looking deeper under the surface it shows that these results are mainly driven by the latter period, 2001-2011. That seems to make sense as these are the most volatile years in their sample and using the threshold strategy is in fact a disguised long volatility play. Holmberg et al. (2013) also note that going further down the tail, by increasing both the upper and lower threshold levels, the success rate and the average return increase. Their finding that the average return increases when increasing the threshold levels seems to be counterintuitive as setting a higher threshold should normally cost the investor a part of his returns since the position is now initiated at a later point. Therefore, our expectation is that there is a tradeoff between threshold levels and returns. The findings by Holmberg et al. (2013) are in sharp contrast to Wang and Xu (2015) who studied the predictability of momentum based on volatility levels and find a negative correlation between the two. The most remarkable about the study done by Holmberg et al. (2013) is that they do not mention, what is perhaps the cornerstone of their methodology, at what levels they set the thresholds. This is of major importance as thresholds that are relatively close to the openings or closing price get passed rather easily while thresholds further away from the openings or closing price aren't.

Also, do they take an absolute number to set the thresholds or is the threshold based on previous stock specific return behavior?

Despite that the study done by Holmberg et al. (2013) comes close to this study it differs in certain ways as we will be working with a high variety of stocks listed on the NYSE for a period of 16 years in contrast to using crude oil futures for a one year period. To the best of the authors knowledge, there are no studies yet investigating the intraday momentum effects for NYSE listed stocks based on a threshold methodology. The results will be useful for investors working with automated trading algorithms that are looking for ways to further improve their profitability. This study will also provide a better understanding of intraday momentum returns to finance literature which knows a relative paucity of intraday studies. Further, we expect that our results will come out significantly different compared to the study by Holmberg et al. (2013) as the futures market is characterized by lower transaction costs and the players on the futures market are relatively better educated or are trading on behave of their firm (i.e. institutional investors like pension funds). Therefore, we are under the impression that it is interesting to look at intraday momentum for NYSE listed stocks.
The main research question we will be working with in this study: *what are the returns for NYSE listed stocks for the years 2000 to 2015 when applying intraday momentum filters and reversal filters based on a threshold methodology.*

II. INTRADAY METHODOLOGY

Through Wharton Research Data Services (WRDS) we have access to the Center for Research in Security Prices (CRSP) which includes, among other, daily stock information. Unfortunately, CRSP does not provide intraday data to its users which would be preferred by the authors since intraday data would give an even better understanding of intraday price trends and would provide the opportunity to broaden the tested strategy (e.g. set stop-losses). However, with the available Open, High, Low and Close price of a stock it is possible to construct an adequate research method that will provide a well substantiated answer to our research question.

Inspired by the methodology proposed in Jegadeesh and Titman (1993) we try to find momentum in the intraday sphere. Jegadeesh and Titman (1993) proposed a ranking method by which every given stock is ranked based on their previous return. They go long in the top performers and short in the worst performers. It may be clear that under this methodology the chances of involvement for any given stock are completely dependent on the performance of other stocks (i.e. on the relative distribution). We are under the impression that when using this methodology possible profitable trades could get excluded from the strategy which could turn out to be rather profitable and perhaps even turn out to be less volatile which would increase the Sharpe ratio. Therefore, we are looking for ways to use the momentum strategy intraday while in the meantime selecting stocks based on individual characteristics instead of on relative peer distributions.

We find the answer in the study by Holmberg et al. (2013) who proposed a rather innovative methodology. The methodology proposed, and the one we will be using in this study, works as follows: based on the opening price an upper and lower threshold will be determined. If this threshold gets "broken" it is assumed that the stock will continue its path in the direction of the break out and a thus a position is taken in that direction. If, for instance, the upper (lower) threshold is broken a long (short) position will be established. Since we do not have access to intraday data it is not possible set stop losses or other barriers to protects ourselves from any downfall or close a position after a certain amount of profit is reached. We therefore assume that any taken position gets closed at day end at the price ruling at that time (i.e. the closing price). For volatile stocks, however, it could be possible to break through both the upper and lower threshold during the day. In those cases, we have a simulated stop-loss since the second position initiated will cancel out the first position as the long and short get balanced out; minimizing the maximum loss from the original position. If for the long (short) position the closing price is above (below) the upper (lower) threshold a profit is made.

Holmberg et al. (2013) unfortunately don't shed light on their approach of setting the threshold levels. As each stock has specific, unique, characteristics it is our believe that the threshold levels should be linked in a way that incorporates this. For example, since each stock has different volatility levels simply setting the thresholds 2% above and below the openings price would be too simplistic (although we will test this methodology as well, see (4) and (5)). The method we propose to link stock characteristics to the threshold levels is based on the average daily return of the last month (i.e. last 20 trading days) which will thus incorporate firm specific characteristics, such as the volatility.

$$\overline{R_i} = \frac{1}{n}\sum_{i=1}^{n} R_{it} \quad (1)$$

Where $\overline{R_i}$[6] is the average daily return for stock i for the previous 20 trading days. R_{it} is the return for stock i on time t. We use a normal distribution to set the different threshold levels based on the average return and test a variety of confidence intervals, namely, 90%, 95% and 99% intervals. The interval methodology therefore looks as follows:

$$\psi_{uit} = P_{oit} * [1 + (\overline{R_i} + z_{\alpha/2}\frac{s}{\sqrt{n}}) \quad (2)$$

$$\psi_{lit} = P_{oit} * [1 + (\overline{R_i} - z_{\alpha/2}\frac{s}{\sqrt{n}}) \quad (3)$$

Where ψ_{uit} stands for the upper threshold for firm i at time t and ψ_{lit} for the lower threshold for firm i at time t. P_{oit} indicates the openings price for firm i at time t. $z_{\alpha/2}\frac{s}{\sqrt{n}}$ is a standard confidence interval formulation where s is the standard deviation of the returns, n the number of observations and $z_{\alpha/2}$ is the Z-score or number of standard deviations from the mean data point and α is the significance level. Using this setup, we incorporate firm specific characteristics in the threshold levels. In contrast, we will also work with a “simple” fixed threshold setting methodology, which is not based on firm specific characteristics, in an attempt to find dissimilarities in both methods. The simple threshold setting looks as follow:

$$\psi_{uit} = P_{oit} * (1 + \tau) \quad (4)$$

$$\psi_{lit} = P_{oit} * (1 - \tau) \quad (5)$$

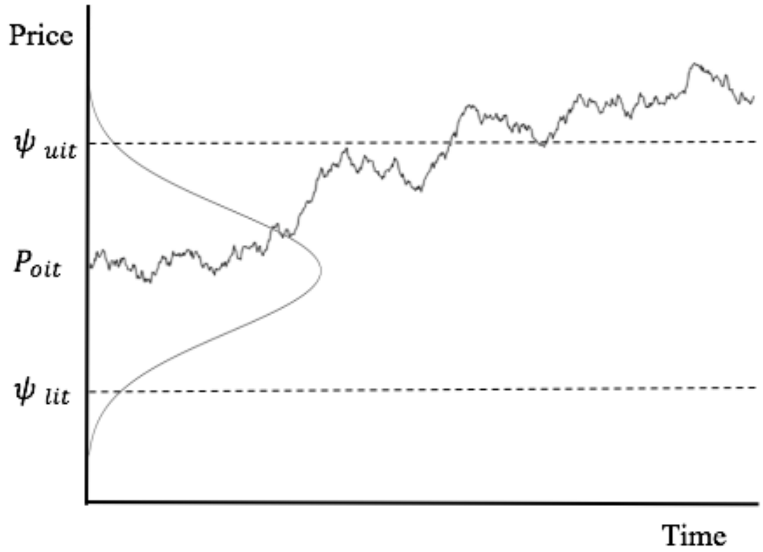
Where τ is a randomly chosen fixed percentage level – in this study we test the thresholds with τ levels of 1%, 2% and 3% respectively. The used threshold setting methodology is graphically shown in Graph I.

[6] Natural logarithms are used for return variables.

Graph I

Methodology

The upper threshold and the lower threshold is set based on a normal distribution around the openings price. 90%, 95% and 99% interval levels will be used. In addition, fixed 1%, 2% and 3% threshold levels will be tested.



In addition to testing our set of threshold levels, which are set beforehand, we will also investigate possible effects of using the previous day's closing price as starting point. Working with the closing price should be interesting because in cases of significant overnight developments the closing and opening price might be significantly different. In those cases, it is possible that a position is initiated immediately at the opening of the market. This immediate position could turn out to be significantly more positive than other initiated positions due to the fact that the new information gets slowly digested throughout the day and day traders in the meantime also trade on the new information. Working with the openings price in these cases could take the filter longer to initiate a position; after which part of the price could already be incorporating the new information. For example, if company A announces pre-opening that it will divest part of its business it takes time for investors and analysts to update their outlook for the company. In case of significant news analysts will update their guidance slowly throughout the day; leading to further price pressures. Therefore, an investor would like to signal trades as early as possible. Furthermore, working with the closing price instead of the openings price will also provide the opportunity to test the dataset for possible reversal patterns.

This would be the case if our momentum returns come out significantly negative as reversal returns are the exact opposite of the momentum returns when using our threshold methodology.

The next step is to set up the methodology that captures the momentum effects. As mentioned earlier, we do not have access to intraday data. Therefore, if a stock breaks through its upper or lower threshold a position is taken which is assumed to be initiated at the threshold level and assumed to be closed at the closing price of that same day. At this point we assume that there are no transaction costs and that there is always sufficient volume to fill our orders. Our returns are therefore overestimating actual momentum returns (which we will address when interpreting the results). The return on an initiated position is thus the difference between the threshold and the closing price.

$$(6) \qquad R_{longit} = \ln\left[\frac{P_{cit}}{\psi_{uit}}\right]$$

$$(7) \qquad R_{shortit} = \ln\left[\frac{\psi_{lit}}{P_{cit}}\right]$$

Where R_{longit} is the return for the *long* position for stock *i* on time *t* and $R_{shortit}$ is the return for the *short* position for stock *i* on time *t*. P_{cit} is the closing price stock *i* on time *t*.

To assess the magnitude of the returns, abnormal industry return methodology is used where one stock is compared against the industry in which it operates for the same day. The abnormal industry return methodology is preferred for our setup because a short time window is used which is easily influenced by daily characteristics (e.g. volatility discrepancies compared to previous periods). If the firm's own historical average return is used to test for abnormal returns, these day specific characteristics would not be included. For example, if our filters would be implemented on volatile days, e.g. Black Friday, testing for abnormal returns based on a previous period's return would give an unfair representation. However, comparing the returns resulting from the momentum strategy to a broad class of common stocks in the same industry for the same day addresses the mentioned concerns.

$$(8) \qquad AR_{it} = R_{longit} - R_{\theta t}$$

$$(9) \qquad AR_{it} = R_{shortt} - R_{\theta t}$$

Where AR_{it} is the abnormal return for firm i on time t and $R_{\theta t}$ is the mean industry return for that same day which is based on all firms operating in the same industry as firm i.

III. DATA AND DESCRIPTIVE STATISTICS

We will be applying our Opening Range Breakout filters to a relatively long period ranging from 2000 to 2015 which is in contrast to other studies using only one year of observations (e.g. Venter, 2009 and Holmberg et al. 2013). This period is interesting for multiple reasons. First of all, working with a recent time period makes the results more relevant for today's investors. Secondly, the number of listed stock on the NYSE increased significantly to over 2,700 listings for 2015 (see Table II), therefore, working with this dataset will provide the highest number of stocks, which makes the results more robust. Thirdly, recent years are characterized by an increasing volume and percentage of algorithmic trading which could have an effect on the momentum returns (Avellaneda, 2011). Lastly, using a long period comes with several advantages (and disadvantages) of which the most important one is that it is also possible to determine if there are macroeconomic factors influencing the intraday momentum returns. Most interesting would be to look how the strategy performed during high volatility years which the markets for instance experienced during the recession of 2008 – 2009[7]. It should also be interesting how the momentum strategy performed during its recovery in the years after the recession as literature pointed out that momentum, using longer time windows, tends to crash right after a recession during the recovery period. The biggest drawback of using a 16-year time period is that we now have to process and analyze well over 7.5 million observations which comes with the necessary hassle regarding IT processing and interpreting. This study will work with 2,732 NYSE listed stocks which are included in the Center for Research in Security Prices database for the year 2015. The bottom decile of stocks by market cap is not used in our analysis as these include the smallest stocks in the dataset that may not be actively traded and may have a long interval without trading or quote adjustments. Additionally, small market cap stocks may be easily manipulated by certain investors.

[7] There are multiple definition of a recession but the one mostly used defines a recession as a period in which GDP declined for two consecutive quarters; which it did for the September 2008 – September 2009 period.

Therefore, bottom decile stocks are excluded to ensure that the results are not driven by infrequent trading, illiquidity or price manipulation.

In order to get familiar with the data and to get a better understanding we walk through several descriptive statistics tables, starting with Table I.

TABLE I

Descriptive Statistics

Overview of industry classification for 2,372 NYSE listed firms used in our dataset (base year 2015). Included are the average spread per industry for the years 2000 (1) and 2015 (2) and their relative improvement (3). Average spread is calculated as the difference between the closing ask and closing bid divided by two. Column (1) and (2) are in USD$.

SIC-code	Industry	# of firms	% of total	(1)*	(2)*	(3)
0-999	Agriculture, Forestry & Fishing	5	0.18%	0.1969	0.0291	85.20%
1000-1999	Mining & Construction	257	9.41%	0.2010	0.0113	94.40%
2000-3999	Manufacturing	655	23.98%	0.2350	0.0154	93.46%
4000-4999	Transportation & Public Utilities	291	10.65%	0.2356	0.0141	94.02%
5000-5999	Wholesale & Retail Trade	180	6.59%	0.2091	0.0155	92.60%
6000-6999	Finance, Insurance & Real Estate	1,021	37.37%	0.2024	0.0152	92.50%
7000-8999	Services	290	10.61%	0.2154	0.0102	95.27%
9000-9999	Public Administration	6	0.22%	-	0.0151	-
9999	Missing	27	0.99%	-	0.0243	-
	Total	2,732	100%	-	-	-
	Average	304	11.11%	0.2136	0.0167	92.20%

(1) Average spread for the year 2000 per firm (1,362 firms)
(2) Average spread for the year 2015 per firm (2,732 firms)
(3) Percentage drop in average spread from 2000 to 2015
* Outliers are excluded

Table I distributes all firms in our database, with base year 2015, by industry using their Standard Industrial Classification (SIC) code. This study will not take into account possible transaction costs and bid-ask spread costs for the simple reason that we do not have access to this data on an intraday basis. Therefore, our results will overestimate the actual momentum returns as costs should be subtracted from the returns found. However, CRSP includes closing ask and closing bid variables from which an average spread can be determined which will provide some flavor as to the height of these costs and will thus indicate how extreme our assumption regarding the bid-ask spread is. The average spread is the difference between the closing ask and closing bid divided by two as this is the average costs an investor would make per trade. From column (1) it follows that for the year 2000 the average spread is 0.2136$ with minor differences between industries. Looking at column (2), the average spread is 0.0167$ for the year 2015 with the Agriculture, Forestry & Fishing industry being the most expensive industry to trade; showing a spread of almost two times the average. Note however that this is based on only five firms. From column (3) it may be clear that new regulations, improvements and increased trading has decreased the average spread significantly to. Over the period 2000 to 2015 the average spread dropped 92.20% on average with, again, the Agriculture, Forestry & Fishing industry lagging behind.

Next to industry classifications (which are more firm specifics) and associated costs of trading, it is also interesting to get a better understanding as to how the period investigated looked like in order to better interpret results later on. Table II gives a deeper insight into how the stock market for the 16 years in our sample performed. Looking at the S&P500 returns, we clearly see the effects of the dot-com bubble starting in 2000 and the housing bubble in 2008 - 2009. The most profitable years seem to be the ones right after the recession during the recovery years and 2013 which almost returned 30%. What is also interesting for our study is how many times a stock closes on its day high or day low. The day high and day low closes indicate, to a certain degree, the possible profitability of our strategy. The strategy used in this study favors extreme outcomes as it sells any taken position during the day at that same day's closing price which makes the extreme closings an interesting statistic to look at. From Table II it follows that the number of high closes and low closes have been steadily decreasing from over 37% combined to less than 8% combined. An explanation for this drop in extreme closes is that due to the increasing level of automated trading and high frequency trading (which is a subset of automated trading) markets became less volatile and stocks therefore close less often on their day high or day low. For instance, insurance companies and pension funds usually place large orders which have a significant impact on the price of a stock. A high frequency trader picks up this order under the impression that he can make a profit as the middleman in the transaction. The high frequency trader splits the large order into multiple smaller orders which will have less price impact and thus reducing stock volatility. Therefore, as stocks have become less volatile over the years and day closings are less extreme, our results could show higher profitability in the earlier years since the market closings are more extreme for that period.

TABLE II

Descriptive Statistics

Number of listed NYSE firms and year specific descriptive statistics. High Close and Low Close display the percentage of observations in the given year that the stock closes on its High or Low. Average Spread is calculated as the difference between closing ask and bid divided by two. Column Average Spread is in USD$.

Year	Firms	High Close %	Low Close %	S&P500*	Avg. Spread**
2000	1,362	19.23%	18.06%	-10.14%	0.2006
2001	1,429	14.49%	11.95%	-13.04%	0.1190
2002	1,505	13.01%	10.67%	-23.37%	0.0937
2003	1,563	12.27%	8.60%	26.38%	0.0483
2004	1,652	10.27%	7.50%	8.99%	0.0328
2005	1,730	8.35%	6.21%	3.00%	0.0332
2006	1,802	7.43%	4.98%	13.62%	0.0294
2007	1,905	6.03%	4.87%	3.53%	0.0334
2008	1,934	5.74%	4.83%	-38.49%	0.0363
2009	1,986	6.28%	3.94%	23.45%	0.0232
2010	2,088	6.44%	3.64%	12.78%	0.0166
2011	2,186	5.32%	3.85%	0.00%	0.0157
2012	2,304	6.00%	3.78%	13.41%	0.0157
2013	2,471	5.21%	3.35%	29.60%	0.0161
2014	2,635	4.48%	3.62%	11.39%	0.0153
2015	2,732	4.20%	3.80%	-0.73%	0.0159

* Calculations do not reflect any dividends paid or any stock spinoffs from the original stock. Taxes and commissions are not factored into calculations[8].

** Outliers are excluded

Furthermore, as already noticed in Table I, average spreads have been significantly declining for 15 years. (Note that comparing the 2000 and 2015 Average Spreads from Table I to Table II shows a discrepancy due to the fact that Table I does not allow multiple observations per company and Table II does allow multiple entries per year).

[8] For returns including dividends, spinoffs, taxes and commissions see: New York University Stern School of Business, 2017

IV. STRATEGY PERFORMANCE

In this section, we will interpret the discovered results using the explained methodology. Table III shows the Abnormal Returns based on the opening price which are tested using a 5% significance level. The shown Abnormal Returns are based on threshold levels that are set using a normal distribution with 90%, 95% and 99% levels respectively. For instance, the AR90% column shows the Abnormal Return for thresholds which are set using a 90% level which is then tested using a 5% significance level. N shows the number of trades made for the period per specific threshold.

TABLE III

Results

The mean Abnormal Returns (AR) for momentum per period which is based on the opening price using a 5% significance level for the different threshold levels which are set at 90%, 95% and 99% respectively. In brackets are T-statistics. N displays the number of positions initiated for the specific period. Please note that the time period categories are not evenly distributed.

	AR90%	N	AR95%	N	AR99%	N
2000-2004	0.0020 (131.7279)***	1,413,192	0.0017 (110.1849)***	1,351,979	0.0013 (75.3306)***	1,178,231
2005-2009	0.0008 (50.2205)***	1,980,590	0.0005 (33.0218)***	1,910,246	0.0002 (10.3774)***	1,685,024
2010-2015	0.0000 (5.0704)***	3,046,954	-0.0001 (-15.5342)***	2,932,229	-0.0003 (-35.7930)***	2,562,251
Full Sample	0.0007 (98.2004)***	6,440,736	0.0005 (64.5021)***	6,194,454	0.0002 (21.2044)***	5,425,506

*, **, *** denotes statistical significance at the 0.10, 0.05 and the 0.01 levels, respectively.

Looking at the results, the first thing noticed is that all Abnormal Returns are highly statistical significant at the 1% significance level. This is in line with expectations as the dataset works with a large number of observations which deflates the standard error. The AR90% has an average Abnormal Return of 0.07% which is based on 6,440,736 trades for the whole period, this comes down to over 1,600 trades per day. If we look deeper to the distribution of this Abnormal Return across time periods it is clear that the return diminishes over time; from 0.20% in the first-time period to 0.00% in the last period. The number of trades per time period increases, this is related to the number of stocks included which increased steadily for our period. Looking at AR95% the same pattern emerges; Abnormal Returns start at 0.17% and range to -0.01% with an average of 0.05% for the whole period. AR99%, once more, shows a same pattern with returns starting at 0.13% and ranging to -0.03% for the latest period with an average of 0.02%. Looking at different thresholds per time period; Table III shows that the number of trades decrease when thresholds are increased. This seems reasonable as stocks now need a higher volatility level to reach and break through the thresholds; leading to fewer trades. As expected, Abnormal Returns also become lower when increasing the threshold levels. The rationale behind the lower Abnormal Returns is that when thresholds are set higher the filters will signal stocks later on in their price movement which decreases the average return as trades are initiated at a later stadium. This is in contrast to what Holmberg et al. (2013) argue that going further down the tail, by increasing the upper and lower threshold levels, would increase the success rate and average return. Almost all Abnormal Returns come out positive and are all highly statistical significant. However, the Abnormal Returns are so small that it will not cover our assumptions that there are no transaction costs, no bid-ask spread costs and there is always enough volume. Therefore, we have to conclude that the results are not economically significant and it is not possible to profitably trade using the set-up filters working with a normal distribution threshold methodology based on the opening price. For space purposes, the same Table based on the closing price, Table VII, can be found in the Appendix. Table VII shows a bit higher Abnormal Returns but eventually leads to exactly the same conclusion: Abnormal Returns decrease when looking at later time periods and overall the Abnormal Returns are too low to cover trading costs.

Table IV works with the second threshold setting methodology which is based on fixed levels and shows Abnormal Returns based on the openings price using fixed threshold levels of 1%, 2% and 3% which are not in any way linked to stock characteristics. Table IV shows a same pattern as that was found in Table III and Table VII (see Appendix): Abnormal Returns are positive and statistical significant but decrease when looking at later time periods. Besides the 3% full sample Abnormal Return, which knows a 5% significance level, all returns are highly statistical significant at the 1% level. Abnormal Returns are almost identical to Table III which is remarkable as it uses a different threshold setting methodology and significantly more trades (over 1,600 a day, for the 90% level, compared to 1,200).

TABLE IV

Results

The mean Abnormal Returns (AR) for momentum per period which is based on the openings price using a 5% significance level for the fixed threshold levels which are set at 1%, 2% and 3%, respectively. In brackets are T-statistics. N displays the number of positions initiated for the specific period. Please note that the time period categories are not evenly distributed.

	AR1%	N	AR2%	N	AR3%	N
2000-2004	0.0021 (119.4893)***	1,132,666	0.0017 (57.8929)***	616,051	0.0013 (27.8070)***	332,603
2005-2009	0.0007 (39.9281)***	1,604,574	0.0002 (6.1094)***	936,822	-0.0002 (-3.3800)***	554,409
2010-2015	-0.0003 (-26.7722)***	2,245,709	-0.0004 (-17.3355)***	1,056,929	-0.0005 (-15.5488)***	513,271
Full Sample	0.0006 (67.9516)***	4,982,949	0.0003 (21.4978)***	2,609,802	0.0000 (1.9276)**	1,400,283

*, **, *** denotes statistical significance at the 0.10, 0.05 and the 0.01 levels, respectively.

The conclusion therefore is that using a fixed threshold setting methodology has no major impact as to the magnitude of the return but does have impact on the number of trades and a lower number of trades is preferred as it will lead to lower trading costs.

Based on Table III, Table IV and Table VII (see Appendix) we conclude that there is intraday momentum on the NYSE looking at the whole period 2000 – 2015. Returns seem to be concentrated in the first few years which can be explained by an earlier suggestion that markets have become less volatile and more efficient. This also comes forward in the fact that stocks nowadays close less on their day high or day low (see Table II). Our momentum returns are consistent with the results found for crude oil futures by Holmberg et al. (2013) and stocks listed on the JSE by Venter (2009) as they find momentum returns in the intraday sphere as well. It is also in line with the arguments of Bysshe (2004) who in his book "Trading the 10 O'clock Bulls" argues that momentum exists as a stock will continue its price movement in the direction of the break. However, our Abnormal Returns are so small that including all necessary costs (i.e. transaction costs, bid-ask spread costs, insufficient volume costs) it is not possible to profitably trade on intraday momentum working with threshold levels based on fixed thresholds or based on normal distribution thresholds. Venter (2009) draws the same bottom line conclusion; returns are too small to cover trading costs. The momentum returns found by Holmberg et al. (2013) are more robust since even after including all the costs their momentum strategy yields an Abnormal Return.

For the first threshold setting methodology, based on a normal distribution of the returns, it is tested whether there is a difference to using the closing price instead of the openings price - no significant differences were found (Table VII, see Appendix). When we now work with the second methodology, based on fixed threshold setting, and test it with the previous day's closing price, remarkable intraday returns are found which are shown in Table V.

TABLE V

Results

The mean Abnormal Returns (AR) for momentum per period which is based on the closing price using a 5% significance level for the fixed threshold levels which are set at 1%, 2% and 3%, respectively. In brackets are T-statistics. N displays the number of positions initiated for the specific period. Please note that the time period categories are not evenly distributed.

	AR1%	N	AR2%	N	AR3%	N
2000-2004	-0.0124 (-3.1e+03)***	1,112,341	-0.0221 (-2.9e+03)***	583,938	-0.0318 (-2.6e+03)***	304,279
2005-2009	-0.0130 (-3.6e+03)***	1,579,073	-0.0229 (-3.2e+03)***	904,994	-0.0329 (-2.8e+03)***	529,810
2010-2015	-0.0122 (-4.6e+03)***	2,223,697	-0.0217 (-4.1e+03)***	1,034,882	-0.0315 (-3.5e+03)***	495,204
Full Sample	-0.0125 (-6.6e+03)***	4,915,111	-0.0222 (-5.8e+03)***	2,523,814	-0.0321 (-5.0e+03)***	1,329,293

*, **, *** denotes statistical significance at the 0.10, 0.05 and the 0.01 levels, respectively.

Table V shows highly statistical significant Abnormal Returns which can be explained by the deflated standard errors due to the high number of observations. The AR1% threshold level knows an average Abnormal Return of -1.25% for the whole period which is at its lowest at the time interval 2005 – 2009 (i.e. -1.3%). AR2% shows a negative Abnormal Return of -2.22% on average which is at its lowest at the time interval 2005 – 2009 (i.e. -2.29%). The 3% threshold level knows an average Abnormal Return of -3.21% which is at its lowest during the

2005 – 2009 interval for which it is -3.29%. The fact that returns are at its lowest during the time period 2005 – 2009 is explained by the phenomenon that momentum tends to crash right after a recession which is confirmed by multiple studies[9][10]. Table V shows that increasing the threshold level by 1% increases the average Abnormal Return by almost the same percentage. The number of trades also drops significantly: from over 1,200 a day at the AR1% level to just over 300 per day for the AR3% level. Table V confirms once more that there is no intraday momentum on the NYSE using the fixed threshold methodology.

The huge negative intraday returns, however, indicate that there are significant intraday reversals happening in respect to overnight price changes which can be profitably exploited. If our filters would, instead of buying stocks in the same direction as the outbreak, sell stocks in the opposite direction of the outbreak the outcome would be the exact opposite of Table V and replace the negative Abnormal Returns for positive Abnormal Returns (for sake of completeness, see Table VIII in the Appendix). Instead of working with momentum equitation (6) and (7) the reversal filters do the exact opposite and returns would be calculated as shown in equations (10) and (11)

$$(10) \qquad R_{shortit} = \ln\left[\frac{\psi_{uit}}{P_{cit}}\right]$$

$$(11) \qquad R_{longit} = \ln\left[\frac{P_{cit}}{\psi_{lit}}\right]$$

In that case the AR3% strategy yields an average daily return of +3.21% working with 1,329,293 trades over the 2000 – 2015 period which comes down to just over 300 trades per day. This return would be more than sufficient to cover all trading costs (i.e. transaction costs, bid-ask spread costs, insufficient volume costs). There are multiple studies documenting price reversals but it has never been documented for such a large time period and at the same time finding such high Abnormal Returns. Table V (and Table VIII in the Appendix) show that increasing the threshold level increases the Abnormal Return of the reversal filter. This means that the larger the overnight price shift the larger the magnitude of the reversal which is

[9] Momentum crashes after a recession because low beta stocks perform rather well during a market downturn and will thus be selected as winners in the formation period. When markets eventually recover high beta stocks will outperform the low beta stocks leading the momentum portfolio to crash.
[10] E.g. Barroso and Santa-Clara (2015), Wang and Xu (2015) and Daniel and Moskowitz (2016)

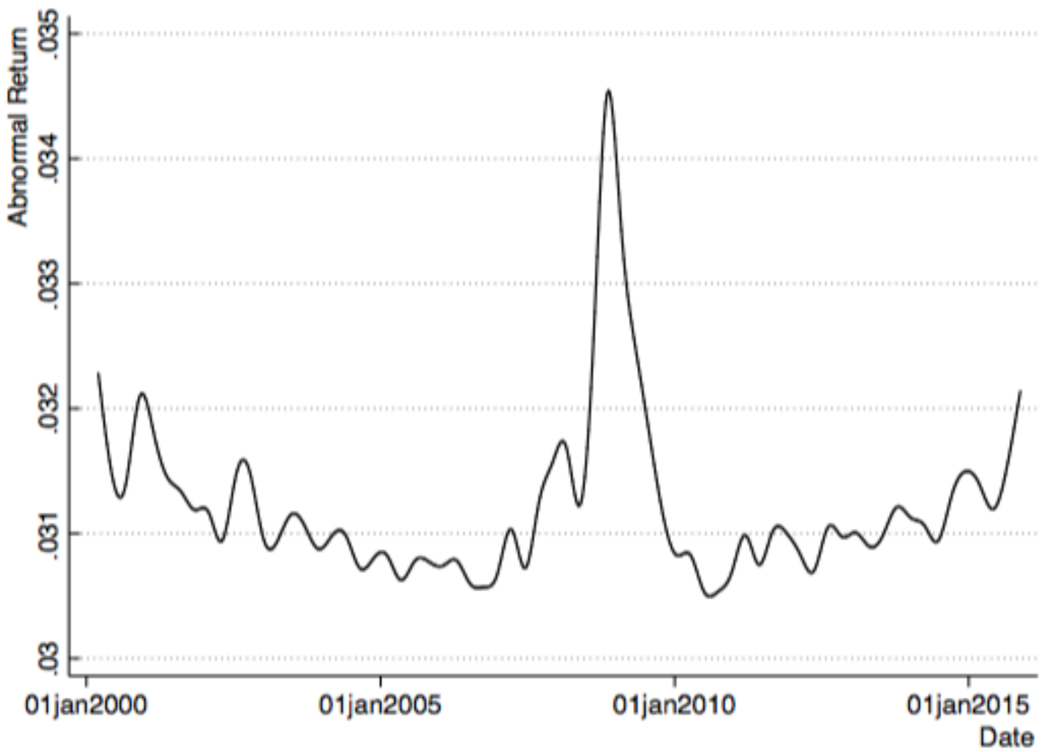
consistent with Fung et al. (2000). Stoll and Whaley (1990) already showed that reversals existed on the NYSE but in a completely different market environment as it focused on the years 1982 – 1986. Stoll and Whaley (1990) and Fung and Lam (2004), in addition, provided evidence that the largest part of a reversal happens in the morning of a trading day. Unfortunately, due to an intraday data constrain we cannot further investigate how the reversals found behave throughout the day but we can take a closer look how it behaves in respect to macroeconomic influences like increased volatility or increasing market efficiencies throughout the 16-year data window.

Graph II shows the Abnormal Return using reversal filters with a 3% fixed threshold level. Once more, please note that the returns using momentum filters, as shown in Table V, are the exact opposite returns compared to using reversal filters.

Graph II

Results

Abnormal Returns working with reversal filters for the years 2000 – 2015 based on a fixed 3% threshold.



Graph II shows the reversal returns based on a 3% fixed threshold methodology (for sake of completeness; Graph III in the Appendix shows the momentum returns). Most notable in Graph II is the peak in reversal returns for the year 2009. This can be explained as momentum crashes right after a recession which is argued in many studies (for a good overview see Daniel and Moskowitz (2016)). Although there is no study yet looking at a short intraday momentum window, our evidence points out that momentum also crashes on an intraday time window right after a recession. This makes sense; as stocks recover high beta stocks will outperform low beta stocks leading to negative momentum returns. Negative momentum returns means positive reversal returns as this is the exact opposite using our methodology. It may be clear that all three threshold levels are comparable as they pick up the same stocks at the same time, AR3% is most profitable from a reversal viewpoint as it works with the most extreme overnight price movements only which is in consistent with Fung et al. (2000). Graph II furthermore is inconsistent with Griffin et al. (2003) who argue that macroeconomic factors don't influence momentum returns since our momentum returns show a significant decrease during the recession period of 2008 - 2009. Based on the results, we agree with Wang and Xu (2015) who studied the predictability of momentum based on volatility levels and find a negative correlation between the two. Also, Graph II shows a minor declining trend up to the recession and a minor upward trend after the recession.

Previous literature (e.g. Kang (2005), Venter (2009) and Verousis and Ap Gwilym (2011)) finds that there is a large difference in momentum returns for large cap and small cap stocks on larger time windows, our data provides no evidence that this is also the case for intraday returns. Our explanation is that intraday returns are less bound by firm specific characteristics, such as market cap. If there are stock characteristics driving momentum or reversal returns we assume that trading characteristics (e.g. spread, volatility or volume) rather than firm specific characteristics (e.g. market cap) are driving these returns.

Table VI looks at differences between high volume stocks and low volume stocks. Abnormal Returns differ slightly as the high-volume stocks know an Abnormal Return of -3.21% and the low volume stocks -3.12%. Although this is statistically significant with a t-statistic of 19.5633, economically this is not a significant difference. What is striking though is that the total number of observations breaking through the AR3% boundary is almost completely originating from high volume stocks (i.e. 1,299,239 out of the 1,329,293 observations). This is inconsistent with Avramov et al. (2016) who argue that liquid markets, and thus higher volume markets, know a higher momentum anomaly. Our explanation is that high volume stocks tend to be less volatile so when there is a large overnight change this is seen as extraordinary by investors which will respond to it in the morning by correcting back towards the original price trend. Low volume stock tends to be more volatile so a large overnight price shift can be seen as a normal event and thus less reversal effects.

TABLE VI

Results

High volume versus low volume comparison. Volume is used as a percentage of outstanding shares after which it is distributed into a high and low group based on the 5th percentile boundary. T-statistics tests the mean from the high-volume group against the low volume group.

Volume Category	Mean	N	T-statistic
High	-.0321	1,299,239	19.5633
Low	-.0312	30,054	19.5633

V. CONCLUSION, DISCUSSION AND RECOMMENDATION

Among existing literature there is a relative paucity of studies looking at intraday time series patterns and profitability (mainly due to intraday data constraints), although the market is clearly moving toward (ultra)short time windows. It is therefore crucial that intraday data is made more easily available in order to start understanding the forever increasing complex algorithms and trading strategies used in the marketplace today. Existing literature finds that momentum returns, based on longer time windows, over time became unprofitable[11].

[11] E.g. Sullivan et al. (1999) for stock markets (DJIA), Olson (2004), Schulmeister (2007A), Schulmeister (2007B) and Frömmel and Lampaert (2016) for exchange markets and Irwin and Park (2005) for multiple future markets.

Therefore, this study took a closer look how *intraday* momentum developed through time. Using an innovative methodology proposed by Holmberg et al. (2013), circumventing the intraday data constraint by using only the daily Open, High, Low and Close price, we investigated how momentum behaves intraday. Original momentum methodology selects stocks based on a relative peer distribution where this study worked with two different types of threshold setting methodologies using the assumption that there are no transaction costs, no bid-ask spread bounces and there is always enough volume to fill an order. The first threshold methodology incorporates stock specific characteristics to set a threshold level, the second threshold methodology works with a fixed threshold level.

Working with 2,732 NYSE listed stocks for the period 2000 – 2015 we find that momentum still exists for the intraday period. The highest momentum return is found when the threshold is based on the openings price for which an intraday momentum return of 0.2% can be achieved. Furthermore, evidence points out that momentum returns have significantly diminished over our 2000 – 2015 period, this is consistent with Table II which shows that markets have slowly became less volatile with less extreme closes. When taking into account unavoidable transaction costs, bid-ask spreads and the assumption that there is always enough volume to fill orders; momentum returns will become economically insignificant and would be negligible which is consistent with the findings by Venter (2009).

Since the used methodology works with thresholds based on the closing price of the previous day or the opening price instead of a relative ranking method the well-known overnight price reversals returns are the exact opposite of the found momentum returns. Therefore, working with a fixed threshold methodology and the previous day's closing price and looking at the returns trough a reversal perspective can yield a maximum daily return of 3.29%, which is highest for the most extreme overnight price shifts. After taking into consideration the possible transaction costs the returns would still be highly economical significant. Results furthermore indicate that momentum crashes right after a period of recession - this is explained by the fact that high beta stocks will start outperforming low beta stock. The reversal returns mainly originate from large companies with high volume stocks. Our explanation for this is that large overnight price changes for large companies, who in general know a slow price movement compared to smaller companies, is seen as a unique event on which investors trade and thus revert part of the overnight shift as it is seen as an overreaction.

The largest drawback in the used methodology is that our study underestimates possible returns since it does not work with intraday data and positions are closed at days end, i.e. no stop losses can be initiated which would benefit the momentum return. On the other hand, the methodology works with assumptions including zero transactions costs which is clearly optimistic and not realistic. This study is an addition to finance literature which knows a relative scarcity of intraday studies. We hope that by demonstrating that by using an innovative methodology, circumventing an intraday data constraint, will encourage others to do the same and slowly close the gap between intraday literature and today's market place which is focused on short term intraday trading. Furthermore, the results found are interesting for investors already active in the intraday time window or for investors looking to move toward a shorter investing window as we provide proof that it is possible to earn a significant intraday return when using the right strategy filters.

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APPENDIX

TABLE VII

Results

The mean Abnormal Returns (AR) for momentum per period which is based on the closing price using a 5% significance level for the different threshold levels which are set at 90%, 95% and 99% respectively. In brackets are T-statistics. N displays the number of positions initiated for the specific period. Please note that the time period categories are not evenly distributed.

	AR90%	N	AR95%	N	AR99%	N
2000-2004	0.0036 (180.5637)***	1,427,900	0.0031 (152.6625)***	1,377,486	0.0024 (109.8927)***	1,225,071
2005-2009	0.0030 (156.8968)***	1,996,560	0.0024 (124.1020)***	1,942,049	0.0016 (78.5480)***	1,753,245
2010-2015	0.0025 (204.4007)***	3,076,021	0.0020 (164.4253)***	2,989,067	0.0014 (108.9619)***	2,691,139
Full Sample	0.0029 (309.5992)***	6,500,481	0.0024 (251.1556)***	6,308,602	0.0017 (168.2277)***	5,669,455

*, **, *** denotes statistical significance at the 0.10, 0.05 and the 0.01 levels, respectively.

TABLE VIII

Results

The mean Abnormal Returns (AR) for reversals per period which is based on the closing price using a 5% significance level for the fixed threshold levels which are set at 1%, 2% and 3%, respectively. In brackets are T-statistics. N displays the number of positions initiated for the specific period. Please note that the time period categories are not evenly distributed.

	AR1%	N	AR2%	N	AR3%	N
2000-2004	0.0124 (3.1e+03)***	1,112,341	0.0221 (2.9e+03)***	583,938	0.0318 (2.6e+03)***	304,279
2005-2009	0.0130 (3.6e+03)***	1,579,073	0.0229 (3.2e+03)***	904,994	0.0329 (2.8e+03)***	529,810
2010-2015	0.0122 (4.6e+03)***	2,223,697	0.0217 (4.1e+03)***	1,034,882	0.0315 (3.5e+03)***	495,204
Full Sample	0.0125 (6.6e+03)***	4,915,111	0.0222 (5.8e+03)***	2,523,814	0.0321 (5.0e+03)***	1,329,293

*, **, *** denotes statistical significance at the 0.10, 0.05 and the 0.01 levels, respectively.

Graph III

Results

Abnormal Returns working with momentum filters for the years 2000 – 2015 based on a fixed 3% threshold. Note that this is the exact opposite of Graph II which uses reversal filters.