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Abstract

Momentum profits are a well known CAPM anomaly, but these profits have large downside potential because of momentum reversals. Investigating how investors could avoid these crashes and increase their momentum returns is this paper's main goal. This paper uses changes in individual and market turnover rate and the Amihud Illiquidity Measure to time momentum reversals and possibly profit from these crashes. These returns are compared to the Winners minus Losers portfolio created by Daniel & Moskowitz (2016). The only portfolio that shows potential to time momentum reversals successfully is the portfolio that looks at changes in market wide Amihud Illiquidity Measure. This portfolio has the highest Sharpe Ratio and outperforms the Winners minus Losers portfolio by Daniel & Moskowitz (2016). The extent and via which relationships the Amihud Illiquidity Measure predicts momentum reversals is unknown and thus for future research.

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Introduction

The CAPM model is one of the most famous models in finance and is still taught today. The model had a number of phenomena that it could not explain, it was flawed. One of these anomalies was the existence of momentum profits. Investing in stocks that previously won and shorting those stocks that had previously lost simply didn't fit the model(Lewellen & Nagel, 2006). In the meanwhile a lot of research has been done investigating these momentum profits and this paper will do so as well.

The main goal of this paper is to see whether there is a relationship between the moment of momentum reversal and changes in stock liquidity and market liquidity. More precisely, this paper will attempt to use liquidity shocks as a timing mechanism in order to either avoid these reversals or exploit them.

Research on the effects of stock liquidity and returns has been widely researched. This has led to the discovery of the liquidity premium. Similarly, momentum has been a widely researched topic. Zooming in on momentum, one key feature of momentum strategies is their occasional crashes. These momentum reversals have more recently been of interest in the scientific community. For example, Daniel & Moskowitz (2016) famously showed that this option-like behavior is mostly caused by shorting losers that gain excessively. Other researchers have attempted to time these crashes with different approaches. Yu & Chen (2011) have used investor overreaction as a timing mechanism, whilst Malitskaia (2019) and Barroso & Santa-Clara (2015) sought their answer in volatility. This paper will combine the fields of liquidity research with momentum research, creating a niche. This paper is also relevant for individual investors who can gain information on how to beat the market using the trading strategies used in this paper, or when to avoid these strategies. The data and proxies used are widely available to the public which adds to the relevance to investors.

The analyses will include all common shares on the NYSE, AMEX or NASDAQ between 2-27-1976 and 12-31-2004. The stocks are placed into deciles based on ranking period returns every month and are held for one month in a value weighted portfolio. This portfolio is also called the Standard Momentum portfolio. The lowest ranked stocks that have a large negative liquidity shock are removed from the portfolio in the Remove Position portfolio, or placed in the highest ranked portfolio in the Reverse Position portfolio. The highest ranked stocks with large positive liquidity shocks move in the opposite direction. This paper will also look at the average of these changes within the market which determines the avoidance of shorting loser stocks.

The next section will provide an overview on the literature regarding the relationship between liquidity and returns, momentum and momentum reversals. On the basis of this literature the hypothesis of this paper will be drawn up. The following section will discuss in depth the data and the methodology applied in this research. After that the performance of all portfolios will be analyzed and a robustness check will be done using the Amihud Illiquidity Measure. After that a brief section will display the differences in crash returns. The final part of this paper will discuss the conclusion followed by the limitations of this paper.

Theoretical Framework

This section will describe the underlying theory and conclusions of the literature regarding the relationship between liquidity and returns, momentum and its reversals and the ability to time these momentum reversals.

Liquidity and returns

Liquidity has been a prominent subject in research regarding stock returns. The main focus in those papers is investigating whether smaller firms have higher returns. Amihud & Mendelson (1986) also investigated the effect of liquidity on returns. They estimated liquidity using bid-ask spreads as the cost for the illiquidity of a stock, where a low(high) bid-ask spread indicates high(low) liquidity. Amihud and Mendelson found that lower liquidity investments have higher expected returns. Something similar was found for smaller companies: smaller companies are less liquid and have higher returns. Lastly, the authors claim long-term investors should invest in illiquid stocks to achieve these higher returns, whilst the traders with shorter horizons should trade stocks and securities that are more liquid. Amihud, one of the authors, is also the man that proposed the Amihud illiquidity measure in 2002 which will be used in this paper. The Amihud Illiquidity Measure (Amihud, 2002) is a widely used proxy for stock illiquidity and is given by the following formula:

$$\frac{1}{N}\sum_{t=1}^{T}\frac{|r_t|}{\$V_t} = ILLIQ$$

where N is the amount of days, rt is the return on day t and $Vt is the traded volume on day t denoted in Dollars.

Datar et al. (1998) took a different route in determining the relationship between liquidity and stock returns yet found evidence that supports earlier claims by Amihud and Mendelson. Instead of using the bid-ask spreads, Datar et al. used the turnover rate as a proxy for liquidity. Their findings include a significant negative relationship between the turnover rate and stock returns. This evidence supports Amihud and Mendelson (1986) as the stocks with a low turnover rate, the illiquid stocks, experienced higher returns. Datar et al. also checked whether there was a January effect in this relationship, for which no evidence was found.
A more recent paper by Narayan & Zheng (2011) tried estimating the liquidity-returns relationship in an emerging stock market, namely China's. The authors used a proxy for liquidity that included trading volume, turnover rate and trading probability. The findings in this paper were inconclusive. Research has also provided a link between market volatility and stock liquidity. A study by Chung & Chuwonganant (2018) found evidence that "the effect of market volatility on individual stock returns depends on how the liquidity of individual stocks reacts to unexpected changes in market volatility."

Momentum and reversals

Momentum returns are a well known market anomaly. Jegadeesh & Titman (1993) have famously shown that a portfolio that goes long on past winners and sells the past losers earns significant excess returns. Yu & Chen (2011) state that there are two possible reasons why momentum strategies work. The first being the presence of market frictions (Barberis, Shleifer & Vishny, 1998) and the second being "behavioral market inefficiency", which includes investor overconfidence (Daniel, Hirshleifer & Subrahmanyam, 1998). A link between market volatility and momentum profits has also been established. Market volatility predicts momentum profits through default probability and is more accurate for loser-stocks. Additionally low-momentum profits follow highly volatile periods (Wang & Xu, 2015). Avramov et al. (2016) more recently showed how momentum profits are larger in liquid markets and unprofitable in illiquid markets.

A momentum strategy is however not flawless. Strategies that are based on momentum occasionally experience significant losses. This phenomenon is called momentum reversal. A large amount of research has been conducted to explore the reasons why and when these reversals happen. Daniel & Moskowitz (2016) did research on momentum crashes and found that the main reason was past losers gaining excessively when markets rebound. To be more specific, Daniel & Moskowitz claim that in a rebounding market with high volatility, past losers have a high up-market beta in comparison to their down-market beta. This difference in betas isn't properly incorporated in the prices of these past-losers which allows for said excessive returns. Luo et al. (2020) sought the cause of reversals in investors gaining information and their overconfidence, which is somewhat in line with Daniel et al. (1998). They conclude that both momentum and reversals could possibly be caused by late-informed investors who are overconfident as a result of their intel, as well as skepticism among these same investors. These investors incorrectly believe that the investors who were informed earlier gained information that was of little use. As a reaction this skeptical group provides "too much liquidity to early-informed investors"(Luo et al., 2020). In reality these investors, as a result of their overconfidence, have a tendency to invest in past-winners, thus increasing momentum. Finally Luo et al. (2020) present decreasing noise trading and increasing the speed in which accurate public information is released as possible ways to prevent momentum reversals.

Timing momentum reversal

Momentum portfolios have optional-like returns (Daniel & Moskowitz, 2016), and as a result researchers have been seeking a way to avoid being vulnerable to this optionality. Yu & Chen (2011) timed momentum reversals by estimating market overreaction regarding certain stocks, as they argued this would lead to reversal. Stocks experiencing overreaction were classified as winner (loser) stocks with a higher (lower) return than their 12 month geometric average rate of return. Yu & Chen reason that this higher (lower) return draws in more momentum traders which in turn increases momentum until an imminent crash. Yu & Chen (2011) conclude that their momentum reversal strategy incorporates information better and show that it has higher returns. Daniel & Moskowitz(2016) following their conclusions on loser-stocks' up- and down-betas propose bear market indicators for timing reversals. Yet other methods were used by Malitskaia (2019), who had past volatilities as a timing mechanism, and Barroso & Santa-Clara (2015) who scaled their momentum portfolio to constant volatility.
Lin et al. (2021) choose yet another method. This model uses moving average indicators to time reversals. Their model proved to be especially effective during the panic states introduced by Moskowitz & Daniel (2016), as the moving average indicators' ability to predict reversals changes with different levels of information uncertainty.

The vast variety of methods used indicates how no consensus has been reached as to which method is correct. One thing is for sure, momentum portfolios can be improved upon.

Research Question & Hypothesis

Following the theoretical framework discussed in the previous section regarding the relationship between liquidity and stock returns, and the the overreaction of investors causing reversals, the main research question of this paper is as follows:

"Can liquidity predict momentum reversals"

This will be investigated by testing the following hypothesis:

Hypothesis 1: Loser stocks having decreased liquidity is a signal of future reversal

Hypothesis 2: Winner stocks having increased liquidity is a signal of future reversal

Hypothesis 3: A negative market liquidity change is a signal of future reversal.

Data

The following section will provide a description of both the data and the methodology used in this paper. Data has been collected from CRSP via WRDS. The sample includes stocks with share code 11 and 10 between january 1975 and december 2004. Share codes 11 and 10 are the ordinary common shares without further definition. The year 1975 was randomly chosen whilst january 2005 was chosen in order to avoid the financial crisis and its aftermath in following years. The returns are the monthly returns provided by the CRSP database.

The price variable is the closing price of the final trading day of the month. If no closing price is known, the bid/ask average is taken as a substitute. If neither is known the observation is dropped. The companies in the sample do not have to be present for the entire 30 years. Firms going bankrupt and disappearing and similarly new firms going public adds to the realism of the sample. Additionally every stock needs to have at least 12 consecutive months of known data in order to create the rolling averages which will be described in the Methodology section. If a stock is missing one observation, the stock can not enter any portfolio unless there is a valid 12 months of consecutive returns. In this sample firms are present that changed their name and at the same time changed tickers. Tickers can also be reused after a certain amount of time. Therefore the firms within the sample are sorted by their PERMNO which is a permanent identification number given by CRPS. All firms are traded on the NYSE, AMEX or NASDAQ. The trading volume used in the sample is the sum of all trades of a stock during the month, given in hundreds. Additionally NYSE and AMEX round off these volumes to the nearest hundred, whilst NASDAQ gives the actual amount. This will most likely result in noise in the results. The volume of trades used for the Amihud measure are calculated based on daily volume and price data. The risk free rate in this paper is the one month U.S. treasury bill and has one observation at the end of the month every month.

Methodology

Liquidity is challenging to estimate as it is influenced by several factors. In order for this research to be relevant to investors, a liquidity proxy that is available to be public is required. For this reason the turnover rate has been used as a proxy in the Reverse, Remove and Market Liquidity momentum models. Using the turnover rate as a proxy for liquidity is the same proxy used by Datar et al. (1998). The turnover rate is defined as the amount of stocks traded within a month divided by the average stock outstanding within that same month. In order to check whether a significant change in stock liquidity has occurred, a rolling average of turnover rates will be established. This moving average will be calculated using the same dates as the ranking of the returns. Additionally the same one month gap is applied here for consistency reasons. When a stock in the month prior to the formation of the portfolio experiences a change of 50% in turnover rate compared to the turnover rate rolling mean, the position is reversed or removed.

This paper will feature 5 momentum portfolios. The first portfolio which other portfolios will be compared against will be the value weighted market portfolio. The returns for this portfolio are provided by the CRPS database. The market portfolio will help verify whether the momentum portfolio is capable of earning excess returns following Daniel & Moskowitz' (2016) methodology. Transaction costs and margin calls will be absent in this paper. For all decile portfolios the first returns will be earned on 1976-02 following an initial investment of 1$. The final returns will be earned 2004-12.

The second portfolio will be the momentum portfolio from Daniel & Moskowitz (2016) and is recreated as follows: the common shares from firms traded on the NYSE, AMEX and NASDAQ are ranked based on their 'ranking period returns'. The ranking period returns are the cumulative returns based on the closing prices of the last day of all months taken into consideration. These months are 12 months until one month before the formation period. The stocks are then split into deciles based on their rank. The portfolio with the highest ranking is decile 10, the portfolio with the lowest rank decile 1. For all models a High-minus-Low (HmL) portfolio will also be constructed that goes long in Decile10 and shorts Decile 1. Every position of a stock will be adjusted monthly and will depend on the value of the corresponding firm at the start of the formation month. The value of the firm is calculated by multiplying the price and the total stock outstanding. Every position is value-weighted. The choice of using value-weighting was that small cap firms have typically higher volatility and are more risky. Giving these firms the same weight as larger less risky firms would introduce a larger amount of risk within each portfolio. This paper does not focus on risk and thus the choice was made to avoid extra risk. The momentum portfolio from Daniel & Moskowitz (2016) shall from this point on be referred to as the Standard Momentum portfolio.

The third model is named the Reverse Position model. This model is a variation of the previously discussed Standard Momentum model. The model is identical until the weights of every stock are assigned in the respective winner(highest decile) and loser(lowest decile) portfolios. Once a stock that was placed in Decile 10 of the Standard Momentum portfolio experiences a 50% increase in stock liquidity, the stock's position is reversed. A stock that was placed in Decile 1 in the Standard Momentum portfolio that experiences a 50% decrease in stock liquidity will also be reversed. In this paper the reversal shall be done through placing the stock in the opposite ranked decile. Thus a winner stock initially in decile 10 shall be placed in decile 1, and the loser stock that has become less liquid enters Decile 10. If in the next month the change in liquidity is within bounds again, the stock will rejoin its former decile. This process could lead to instances where stock A moves from decile 10, to 1 and back to 10 within 3 months. Again all the portfolios are value weighted. The intuition behind changing deciles after a liquidity shift is that this shift could indicate a momentum reversal. This paper changes its position in the stock a month after witnessing this shock and afterwards incorporates this shock into its turnover rolling mean.

The fourth model shall again differ from Daniel & Moskowitz(2016) in assigning stock weights and is similar to the Reverse Position model. The main difference to model 3 is that instead of reversing the position of a stock that experienced a change in liquidity, the position is set to 0 and no investment into this stock will take place. For this reason this model will be named the Remove Position model. It is important to note that the stock is only left out during the formation period and can be invested in again in other months. The intuition behind model 4 is attempting to avoid stocks that are more likely to reverse. The Reverse Position model has the risk of loser stocks that keep losing entering winner portfolios and consequently lowering the value-weighted return. At the same time, winner stocks that continue winning could enter loser portfolios and increase the value-weighted return. The Remove Position model gives up on the upwards potential of the Reverse Position model in favor of eliminating the downward potential.

The fifth model will take a more wider approach. The previous models included individual stock movements. This model will use the average of liquidity changes to determine market liquidity shocks. This mean is equally weighted because this paper wanted to put more emphasis on small cap companies that tend to be less liquid. Furthermore the portfolio within this model will feature the returns of the Standard Momentum portfolio and when the market liquidity condition is met, the HmL portfolio will turn into a portfolio that only goes long in Decile 10. In this paper this liquidity condition is satisfied when the mean of all differences in liquidity compared to the rolling mean falls below -10% for that month. Using the same measure for liquidity as in the previous portfolio was done for the purpose of being consistent.

Standard Momentum portfolio performance

This section shall present the performance of the Standard Momentum portfolio following Moskowitz Daniel(2016) for the time period 1976-02 until 2004-12. For illustration purposes Figure 1 shall display the cumulative returns of both the highest and lowest decile, as well as the risk free rate, the market returns and the High minus Low portfolio. In order to test whether the Standard Momentum portfolio is capable of outperforming the market, the Standard Momentum portfolio's returns in excess of the risk free rate are regressed on the excess returns of the market. The regression is given by:

$$R_{i,t} - r_f = \alpha_i + \beta_i (R_{m,t} - r_f) + \varepsilon_{i,t}.$$

where $R_{i,t} - r_f$ is the portfolio's excess return and $R_{m,t} - r_f$ is the market's excess return. In this regression the beta signifies how a decile's excess returns move with the excess returns of the market. The alpha displays whether there was underperformance(negative alpha) or outperformance(positive alpha) on average.

In accordance with previous literature, Decile 1 displays the worst returns. Decile 1 averaged an annualized return of -7.7 % and reached an (in this sample) all time low of -97.2% cumulative return. Furthermore Decile 1 had an unconditional CAPM beta of 1.54 and an annualized alpha of -19.2%. Both the market and the risk free rate expectedly outperformed Decile 1 with respective annualized returns of 12.6% and 6.1%. Decile 10 annualized 19.5%, had a beta of 1.32 and had an annualized alpha of 5.69%. Lastly the High-minus-Low portfolio earned the highest annualized returns standing at 20.6% with a beta indistinguishable from 0 and an annualized alpha of 19.3%. The key statistics are displayed in table 1.

Figure 1 also shows sharp declines following periods of positive returns of the High-minus-Low portfolio. These declines are the momentum reversals. To serve as an example, between 10-31-2002 and 11-29-2002 the HmL portfolio had lost 51.2% of its value. This crash was mostly the result of the shorting of Decile 1, which had a sharp rebound. This decile gained 24.4% and 39.5 % in these two months. This finding is in accordance with Daniel & Moskowitz (2016).

Momentum portfolio with reverse positions performance

This section shall discuss the performance of the Reverse Position portfolio. Figure 2 displays the cumulative returns for the winner and loser portfolio, as well as the cumulative risk free rate, market return and the winner-minus-loser portfolio. Decile 1 had an annualized return of 10.1% whilst decile 10 had an annualized return of 18.9%. The market portfolio and risk free rate are the same as in the previous section. The HmL portfolio that shorts the improved Decile 1 annualized a lower return as compared to its Standard Momentum counterpart with +5.8%. In order to test whether the Reverse Position portfolio is capable of outperforming the market, the same type of regression as performed in the Standard Momentum portfolio will be used. The results are displayed in table 1. The regression yields both an insignificant alpha and beta for the HmL portfolio. Similarly, no significant alpha was found for Decile 1. Decile 10 on the other hand yields a slightly significant alpha. Additionally the annualized Sharpe Ratio of Decile 1 which had a slightly negative value(-0.26) in the Standard Momentum portfolio, has now become 0.27. The HmL portfolio on the other hand went from 0.59 to 0.072. Decile 10's Sharpe Ratio stayed almost the same. In order to formally test whether changing from a normal momentum portfolio to the reverse portfolio leads to improvement (or deterioration) of returns, an additional regression will be performed regressing the Reverse Position Decile 1, 10 and the HmL on their Standard Momentum counterparts. The regression will be given by

$$R_{i,t} - r_f = \alpha_i + \beta_i (R_{std\,i,t} - r_f) + \varepsilon_{i,t}.$$

where Ri,t -rf is the excess return of the Reverse portfolio, and Rstdi,t - rf is the excess return of the Standard Momentum portfolio counterpart. The alpha indicates the average difference in excess returns. The results are displayed in table 2. This regression verifies that Reverse Decile 1 has a significantly positive change in returns with an unconditional annualized alpha of 13.0%. The alpha for Decile 10 is insignificant and the HmL yields an annualized alpha of -6.5%. These changes show why the Reverse HmL fails to produce evidence of being able to outperform the market. The portfolio shorts a portfolio with much higher returns as compared to the Standard HmL portfolio.

Momentum portfolio with removing positions performance

This section shall continue with discussing the performance of the portfolio with removing positions. Recall that stocks that had their position reversed in the Reverse Position portfolio, are now left out of the portfolio altogether. The cumulative returns of this portfolio is displayed in Figure 3.

Decile 10 annualized a return of 19.9% whilst decile 1 lost 6.5% annualized. The HmL portfolio annualized 18.8% during the same period. Figure 3 displays the cumulative returns. These annualized returns are seemingly an improvement in comparison to the reverse position portfolio, but are suggestive of being lower than the Standard Momentum portfolio.

In the regression of excess returns on market excess returns, the results are very similar to that of the Standard Momentum portfolios. Decile 1 underperforms the market whilst Decile 10 and HmL outperform it. Except for minor differences in the size of the alphas and betás, the main difference is the beta of the HmL portfolio which is now significant. When testing whether each portfolio out/under-performs its Standard Momentum counterpart, the regression presented a positive alpha for Decile 1. This means that also in the Remove Decile 1, the opposite of the desired effect was observed. The Remove Decile 10's alpha was insignificant. Lastly and most importantly, the Remove HmL portfolio yields a negative alpha. This result is most likely caused by the higher returns in Decile 1. The effect Decile 10 had on this underperformance is unclear.

Market liquidity as timing mechanism performance

This part shall present the results of implementing the fifth model. The only difference of this HmL portfolio to that of the Standard Momentum portfolio, is that the returns are occasionally not partially earned by shorting Decile 1. Following the methodology, this occurred 39 times. The cumulative returns are displayed in Figure 4. This attempt to avoid reversal annualized a return of 20.9%, had an insignificant unconditional beta and an annualized alpha of 18.2%. These numbers are not far off the Standard Momentum HmL portfolio. The Sharpe ratio saw a slight increase but this was not of small magnitude. The alikeness of these portfolios is once again shown in the regression that holds the Standard HmL portfolio as the benchmark, no significant alpha was found and thus no evidence is found that these portfolios differ.

Robustness

In order to check whether the results of all portfolios are dependent on which liquidity proxy is used, this section will summarize the results of the same analysis done previously with the Amihud Illiquidity measure instead of turnover. The results are displayed in tables 3 and 4.

For the Reverse position portfolios, the results generally match. The Reverse Decile 1 experiences an increase in Sharpe Ratio, has an insignificant alpha and a beta close to 1.4. Decile 10 on the other hand has a lower sharpe ratio and yields no significant evidence of outperforming the market. The HmL portfolio does provide a slightly significant negative alpha which would indicate inferiority to the Standard HmL portfolio. This inferiority was already suggested by the very low Sharpe Ratio that was found in the Reverse Position portfolio based on turnover rates.

The Remove position portfolios follow the exact same patterns as described earlier. Remove Decile 1 still underperforms the market, whilst Remove Decile 10 and the HmL portfolio both outperform it. There is no evidence supporting either out- or underperformance of the Remove portfolios compared to the Standard Momentum portfolios.

For the Market Liquidity timing portfolio, the results differ significantly from that of the Turnover proxy. It is firstly worth noting that for the Market liquidity condition to be met, the average Amihud Illiquidity Measure change within a month, needs to be bigger than +10%. This caused the portfolio to avoid shorting Decile 1 135 times. This version of the portfolio annualized a return of 28.7%, which exceeds that of the Standard Momentum HmL. The annualized alpha is on the contrary lower. Additionally the annualized Sharpe Ratio of this portfolio is the highest in this paper, standing at 0.91. Figure 4 displays this portfolio's cumulative return alongside the Standard Momentum Portfolio’s HmL. In the regression holding the Standard HmL as a benchmark, this version of the Market Liquidity timing portfolio manages to produce a significant positive alpha which further indicates this portfolio’s superiority to the previously analyzed portfolios.

Changes in crashes

This section shall present the previously discussed portfolios’ abilities to avoid crashes. Due to the usage of monthly returns, every crash that has occured has only a limited amount of observations. As such, the 15 highest returns of Decile 1 of the Standard momentum portfolio are placed next to each other. As mentioned in the Literature section, the short side of the portfolio gaining excessively is the biggest reason for momentum crashes (Daniel & Moskowitz, 2016) and Decile 1’s 15 largest gains are therefore characterized as momentum crashes. All the compared returns are presented in table 4. This is a non-normally distributed sub-sample which prevents the use of a t test.To verify this a Shapiro-Wilk Test was conducted. This test formally rejected normality ($p<0.05$) Increasing the number of highest returns from 15 to 25 did not change the outcomes of the Shapiro-Wilk Test. Adding a further amount of highest returns of Decile 1 would lead to un-crash-like returns of the HmL portfolio. Additionally the differences in returns to the Standard Momentum HmL does not follow a symmetrical distribution. For these reasons, the sign-test will be used. This test will show whether the median of differences of the HmL portfolios to the Standard HmL is different from 0. This does not take into consideration the size of improvement.

Firstly, one observation from table 5 is that both Reverse Position portfolios perform better during crashes. These positive differences are most likely the result of going long in stocks that were previously in Decile 1 and entered Decile 10. Due to the already shown inferiority of these portfolios to the Standard Momentum portfolio, the differences in crash returns can not be ascribed to the ability to time reversals, but rather going long in stocks that will at some point reverse.

Secondly the Remove Position portfolios are more ambiguous. Using Turnover as a proxy, this portfolio hardly differs from the Standard HmL. The insignificant sign test supports this. Using the Amihud Illiquidity Measure as a proxy offers higher returns than the Standard HmL on 10 out of 15 occasions, but lower returns during the other 5. The sign test does not produce significant evidence here.

The Market Liquidity portfolio that uses Turnover Rate as a proxy, only has one change compared to the Standard HmL portfolio. Though this meant an increase of about 25 % points, it is most likely this change is based upon luck rather than the ability to time reversal. Using the Amihud Measure as proxy on the other hand improves returns during 12 of the 15 crashes. During the other 3 crashes the portfolio doesn't perform worse as well. Though this section can not provide hard evidence, the significant sign test is an indicator that this method has potential. Alternatively this improvement can be ascribed to luck as avoiding a short position in Decile 1 occurred 38.9% of the time.

Conclusion

Momentum profits have occasional crashes. This paper has attempted to time these momentum reversals using liquidity as a potential indicator.

The first hypothesis stated that a loser stock that experiences a decrease in liquidity signals reversal. This hypothesis was tested by the removal of a loser stock from the loser portfolio when it became less liquid. This paper has found that removing these loser stocks results in higher returns of the loser portfolio. Essentially, more extreme loser stocks were removed from the portfolio. If liquidity was successfully timed, the returns of the loser portfolio should have decreased. The second hypothesis stated that winner that winner stocks experiencing positive liquidity changes signals reversal. This hypothesis was tested by removing these stocks from the winner portfolio. No significant difference was found between this winner portfolio and that of the Standard Momentum portfolio. The resulting Remove HmL portfolio still outperformed the market but underperformed its Standard HmL predecessor. Additionally no evidence was found that indicates an improvement in returns during crash periods. This means that during this sample period, 50% increases in Turnover Ratio for winner stocks and 50% decreases in Turnover Ratio fail to time momentum crashes. This also means that the portfolios that attempt to profit from the Remove position portfolios' ability to time reversals, have failed. This was also observed in the analysis of these Reverse portfolios. The Amihud Illiquidity Measure could also not deliver evidence indicating avoidance of crashes. Thus no evidence was found in support of these two hypotheses.

The third hypothesis stated that “A negative market liquidity change is a signal of future reversal”. This paper looked at 10% (or bigger) decreases compared to the rolling average of liquidity. The findings from the Turnover proxy suggested that avoidance of shorting Decile1 during these liquidity shifts resulted in a portfolio indistinguishable to the Standard Momentum Portfolio. There is an argument that using Turnover as a proxy for liquidity does not provide enough information about said liquidity. This can be said because studies have shown different results with different liquidity proxies(Marshall, 2006). The use of the Amihud Illiquidity Measure that uses the same 10% or higher shifts in illiquidity managed to avoid most of the momentum reversals during this sample and offered higher returns than the Standard HmL portfolio. Additionally it produced a much higher Sharpe Ratio which indicates a higher risk-adjusted return. Combining these observations there is evidence that market liquidity can be used to time momentum reversals. One could argue that due to the high frequency of avoiding shorting the loser portfolio, the avoidance of crashes is bound to happen. The extent to which the used method is capable of timing momentum reversals is beyond the scope of this paper.

Limitations & Future Research

Lastly this section will present an overview of what this paper lacked and which can be improved upon in further research. Firstly, this paper uses monthly returns. Daily returns could have provided this paper with more accurate returns during periods of reversal as there would be more observations. Secondly this paper ignores transaction costs. This means that whether a portfolio is capable of beating the market is in reality dependent on the influence of these transaction costs. Thirdly, this paper uses value weighting in its portfolios. This will almost definitely have placed a bias to high cap firms in determining the monthly returns of every portfolio. An equal weighted portfolio would probably have resulted in higher systematic return, but these returns would have had “higher exposure to value, size and market factors”(Plyakha et al. (2021), which the value weighted portfolio avoids. Furthermore this paper has used rounded off volume data which introduces noise into the weighting of returns within Deciles 1 and 10. This paper also uses a relatively short period, spanning 29 years. The sample also stopped at the end of 2004, which means that the conclusions drawn in this paper may not apply to the current market. Another limitation of this paper is that the section Changes in Crashes uses the sign test in order to compare crash returns. This test has very few assumptions which makes it a weak test to use. Future research could also introduce other liquidity proxies into this methodology as this paper limits itself to widely available ones. Another addition could be to use multiple proxies at the same time and to check for different values. This paper limited itself to 50% increases and decreases for the Remove and Reverse portfolios and 10% for Market Liquidities, but there could be an unknown optimal value.

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Appendix

Table 1

Regression results in comparison to the market

Key Statistics	Alpha	Beta	R-Rf	Sharpe
Standard Decile 1	-19.61988 *** (-4.73)	1.539286 ***	-13.78	-0.26158
Standard Decile 10	5.69016 ** (2.11)	1.31672 ***	13.41	0.608467
Standard HmL	19.28448 *** (3.49)	-0.21742	17.061	0.591011
Reverse Position Decile 1	-2.71176 (-0.92)	1.393617 ***	3.97	0.273826
Reverse Position Decile 10	5.0466 * (2.24)	1.323157 ***	12.80	0.591074
Reverse Position HmL	1.737 (0.52)	-0.06525	-0.29	0.072086
Remove Position Decile 1	-18.35292 *** (-4.33)	1.562814 ***	-12.62	-0.21369
Remove Position Decile 10	5.97756 ** 2.24	1.30602 ***	13.73	0.622625
Remove Position HmL	18.30492 *** 3.24	-0.2516447 *	12.71	0.536114
Market Liquidity HmL	18.22404 *** 3.34	-0.05841	14.76	0.604649

Note: These portfolios are created using the turnover rate as liquidity proxy. The alphas and betas are the results of the regression of every portfolio's monthly excess return on the monthly excess returns of the value weighted CRPS index between 2-27-1976 and 12-31-2004. The alphas are in percent and annualized. The R-Rf is the difference in annualized return between the portfolio and the 1-month treasury bill in percent. The Sharpe Ratio is annualized. Between brackets are the corresponding t stats. * Means p <0.1, ** means p < 0.05, *** means p<0.01.

Table 2

Portfolio performance in comparison to the Standard Momentum portfolios

Key statistics	Alpha	Beta
Reverse Position Decile 1	12.97992 *** (-4.44)	0.6636195 ***
Reverse Position Decile 10	-0.29448 (-0.48)	0.9800056 ***
Reverse Position HmL	-6.49704 *** (-2.94)	0.4381454 ***
Remove Position Decile 1	1.56468 *** (-2.73)	1.015031 ***
Remove Position Decile 10	0.44208 (0.85)	0.9847212 ***
Remove Position HmL	-1.52472 * (-1.83)	1.016895 ***
Market Liquidity HmL	1.5198 (0.74)	0.9188369 ***

Note: These portfolios are created using the turnover rate as liquidity proxy. The alphas and betas are the results of the regression of every portfolio's monthly excess return on the monthly excess returns of the standard momentum counterpart between 2-27-1976 and 12-31-2004. This means that Reverse Position Decile 1 is regressed on Decile 1 of the standard momentum portfolio, Reverse Position Decile 10 on Decile 10 etc. The alphas are in percent and annualized. The corresponding t stats are given between brackets. * Means p <0.1, ** means p < 0.05, *** means p<0.01.

Table 3

The underperformance and outperformance of the Amihud Illiquidity Measure Portfolios against the market

Table 3: Amihud Illiquidity Measure market excess

Key Statistics	Alpha	Beta	R-Rf	Sharpe
Reverse Position Decile 1	1.06104 (0.36)	1.368624 ***	7.98	0.407037
Reverse Position Decile 10	1.932 (0.82)	1.365303 ***	9.57	0.478222
Reverse Position HmL	-5.1546 * (-1.92)	0.001827	-6.37	-0.35015
Remove Position Decile 1	-16.30896 *** (-4.21)	1.418563 ***	-10.84	-0.20198
Remove Position Decile 10	5.75592 ** (2.10)	1.30004 ***	13.37	0.608886
Remove Position HmL	16.03932 *** (3.16)	-0.11337	12.70	0.55696
MarketLiquidity HmL	18.4452 *** (4.00)	0.5872899 ***	22.60	0.909193

Note: These portfolios are created using the Amihud Illiquidity Measure. The alphas and betas are the results of the regression of every portfolio’s monthly excess return on the monthly excess returns of the value weighted CRPS index between 2-27-1976 and 12-31-2004. The alphas are in percent and annualized. The corresponding t stats are between brackets. The R-Rf is the difference in annualized return between the portfolio and the 1-month treasury bill in percent. The Sharpe Ratio is annualized. * Means p <0.1, ** means p < 0.05, *** means p<0.01.

Table 4

The Amihud Illiquidity Measure portfolio performance against the Standard Momentum portfolios

Key statistics	Alpha	Beta
Reverse Position Decile 1	0.0126844 *** (3.76)	0.5058295 ***
Reverse Position Decile 10	-2.05632 (-1.13)	0.9106523 ***
Reverse Position HmL	-5.33652 * (-1.85)	0.0110046
Remove Position Decile 1	1.11288 (0.48)	0.8446282 ***
Remove Position Decile 10	0.32664 (0.34)	0.9748673 ***
Remove Position HmL	1.19028 (0.44)	0.791889
Market Liquidity HmL	13.74228 *** (-3.34)	0.5032386 ***

Note: These portfolios are created using the Amihud Illiquidity Measure. The alphas and betas are the results of the regression of every portfolio’s monthly excess return on the monthly excess returns of the standard momentum counterpart between 2-27-1976 and 12-31-2004. This means that Reverse Position Decile 1 is regressed on Decile 1 of the standard momentum portfolio, Reverse Position Decile 10 on Decile 10 etc. The alphas are in percent and annualized. The corresponding t stat is between brackets. * Means p <0.1, ** means p < 0.05, *** means p<0.01.

Table 5

Differences in crash returns

Date	HmL Reverse Position (Turnover)	HmL Remove Position (Turnover)	HmL Market Liquidity (Turnover)	HmL Reverse Position (Amihud)	HmL Remove Position (Amihud)	HmL Market Liquidity (Amihud)
1/31/2001	35.21	-0.72	0	57.39	27.23	43.01
11/29/2002	25.57	3.39	0	35.76	-4.01	39.51
2/28/1991	20.86	-1.12	0	19.16	9.30	32.28
11/30/2001	7.28	-1.49	0	40.19	13.05	30.21
10/31/2001	9.46	0.80	25.90	30.50	10.98	25.90
10/31/2002	4.12	-1.72	0	32.79	10.93	24.37
5/30/2003	6.08	-1.13	0	6.68	-2.85	0
4/30/2003	5.24	-1.25	0	11.39	-0..12	0
1/31/1985	11.06	0.68	0	13.69	-01.80	22.19
5/30/1997	12.93	-2.00	0	14.23	7.07	21.94
4/30/2001	8.42	-7.96	0	16.18	13.78	20.14
4/30/1999	6.36	-2.35	0	16.11	4.31	17.67
1/30/1987	6.31	1.23	0	-1.24	-1.56	17.49
10/30/1998	2.52	-4.20	0	15.66	2.92	16.94
11/29/1996	7.87	-0.97	0	10.53	-4.74	0
Sign Test P value	0.0001	0.1185	1	0.001	0.6072	0.0005

Note: Behind brackets is which method was used as liquidity proxy, for (Turnover) the differences in turnover rate were used, for (Amihud) changes in the Amihud Illiquidity Measure was used. Differences are calculated by subtracting the Standard HmL's return on a given date from the portfolio in the header. The differences are in percentages.

Figure 1: Standard Momentum Cumulative Returns

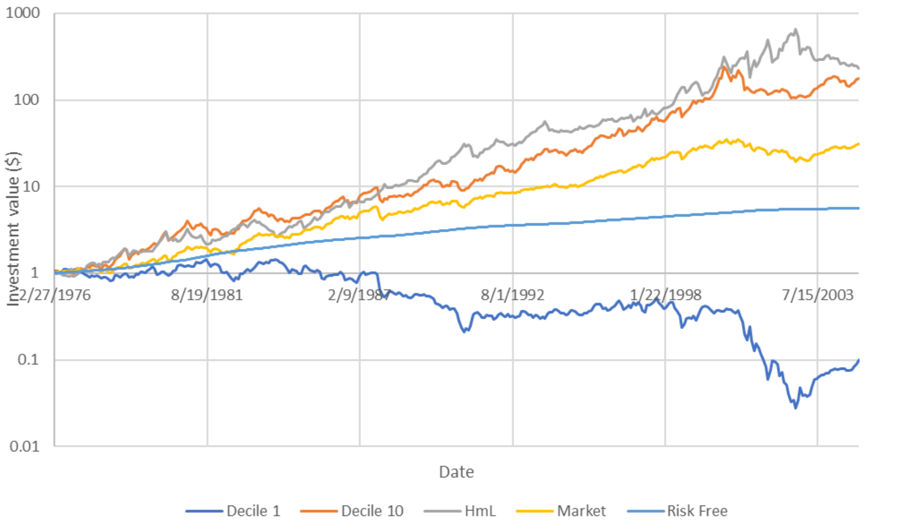
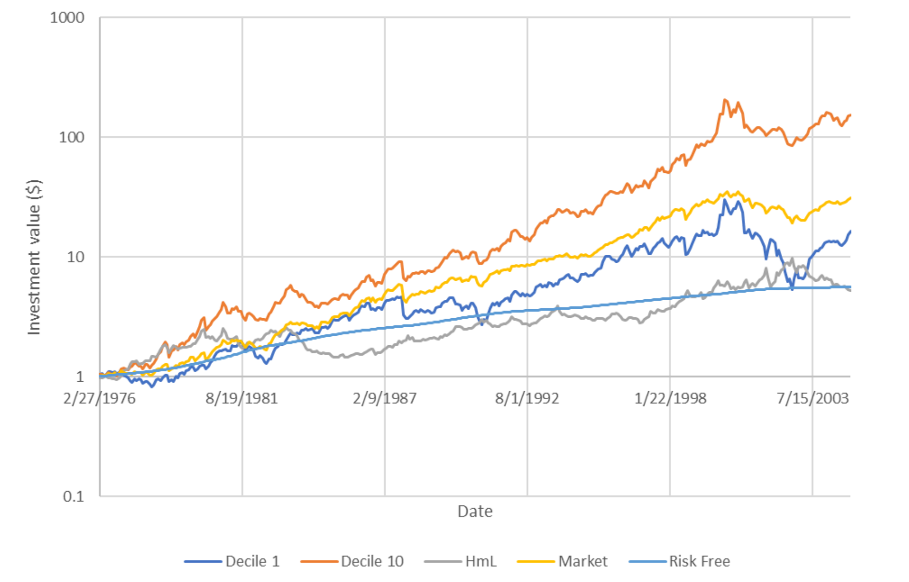


Figure 2: Reverse Position Momentum Cumulative Returns



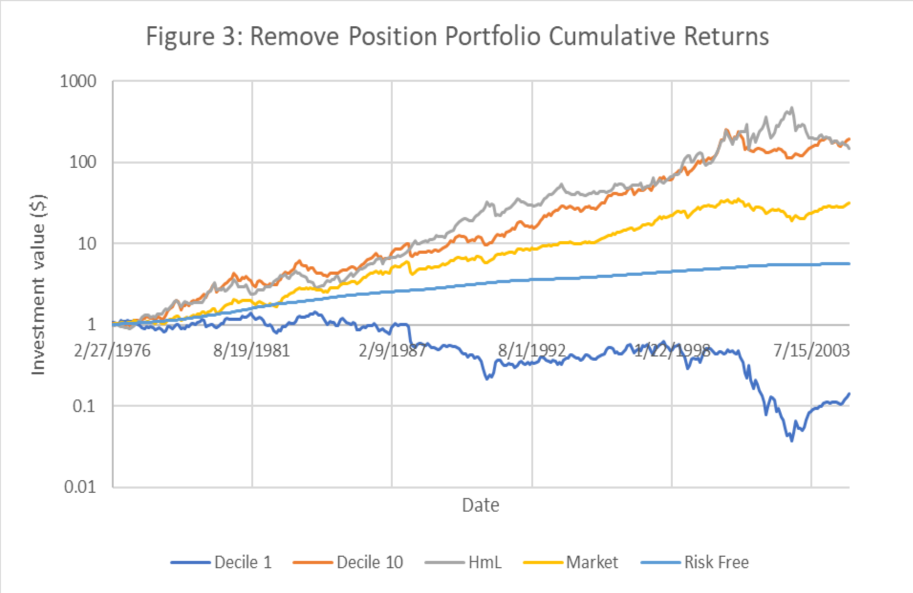


Figure 3: Remove Position Portfolio Cumulative Returns
1000
100
10
1
0.1
0.01
Investment value ($)
2/27/1976
8/19/1981
2/9/1987
8/1/1992
1/22/1998
7/15/2003
Date
Decile 1
Decile 10
HmL
Market
Risk Free

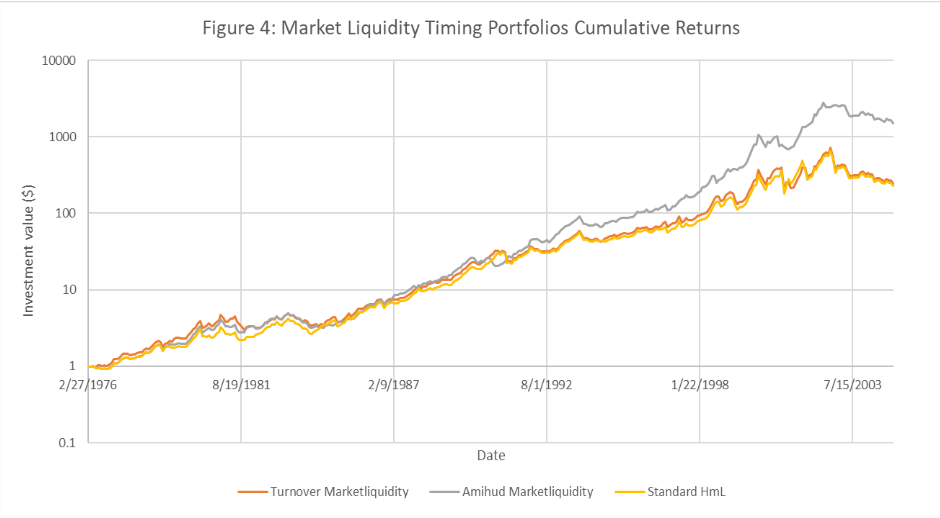


Figure 4: Market Liquidity Timing Portfolios Cumulative Returns
10000
1000
100
10
1
0.1
Investment value ($)
2/27/1976
8/19/1981
2/9/1987
8/1/1992
1/22/1998
7/15/2003
Date
Turnover Marketliquidity
Amihud Marketliquidity
Standard HmL