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## Overreaction Hypothesis with Extreme Market Events for the US Market.

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## Abstract

This thesis investigates the Overreaction Hypothesis in the entire US stock market from 1980 to 2022, employing single and double sorting methods for constructing contrarian investment portfolios. The single sorting procedure showed weak results with a 20-Day lookback period, but a reduction to 10 or 5 Trading Days revealed robust reversion across all size segments. Quintile portfolios of Loser and Winner stocks from single sorting on Total Excess returns exhibited biases in characteristics like Market Equity, Net Income to Market Equity, Book Equity To Market Equity, Realized Volatility, and Amihud Illiquidity metric. The adoption of double sorting procedure, in line with the Fama-French Three Factor Model, confirmed monotonic average returns for the contrarian investment strategy, reinforcing the presence of reversion in the US stock markets. The study addresses the question of whether a regular investor can profit from Overreaction Hypothesis, considering risk, liquidity, and size. The findings suggest that, with a substantial capital investment and careful consideration of these factors, a regular investor can indeed profit from the contrarian strategy, yielding a significant positive alpha on a month-by-month basis. The thesis recommends future research to explore the impact of transaction costs on the profitability of the contrarian strategy, particularly focusing on high turnover and illiquidity ratios that may lead to elevated bid-ask spreads.

**Keywords:** Overreaction, Investment Decisions, Asset Pricing, Rate of Return, Securities Markets

**JEL Classification:** G10,G11,G12,G14,G41

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# 1 Introduction

In this day and age, there is no single country that has been exempt from experiencing some form of economic crisis caused by the outbreak of the most vicious virus (Covid-19) of the past one hundred years, leading to the contraction of the economies. The ensuring rate-hike to fight inflation and the Ukrainian War have all stacked-up against the bullish incentive in the financial markets. These factors have cast a shadow over the post-pandemic recovery for developing and emerging markets. Nevertheless, it appears that the financial markets have accurately assessed the potential adverse economic consequences. However, evidence from a recent study indicates the underreaction of the markets around the announcement of the pandemic (Khatatbeh, Hani and Abu-Alfoul, 2020). The continuously changing conditions in the markets create shockwaves that lead to various ways of earning the abnormal returns as an effect of overreacting or underreacting. It has also been shown that the fluctuations of daily profits from existing investments can have an excessive impact and influence on the market, as observed by J.M. Keynes in De Bond and Thaler (1985). The Efficient Market Hypothesis has been challenged by De Bond and Thaler (1985) with their findings using the contrarian strategy, which states that an investor buys past bad performers (losing stocks) and sells past good performers (winning stocks) with a holding period of three to five years resulted in positive returns for losing stocks and negative for winning stocks in the period of three to five year going forward. The stock prices have been pushed away from fundamental value due to overreaction also called the Overreaction Hypothesis by De Bond and Thaler (1985). Basically, this means that the contrarian investor will invest (long) if he believes the stock price of a company is undervalued and if overvalued he will take a short position. To be able to make profit the markets should have a mean reversion pattern, it is believed that the highest and the lowest prices of the stock is temporary and the price will mean revert to an average in a span of couple of years (Poterba and Summers, 1988). Not everybody supported that idea, and opponents claimed that abnormal risk-adjusted returns in the contrarian strategies are caused by failed risk-adjustment of returns (Chan, 1989). Others argue that the abnormal returns come from the Small Firm Effect where smaller firms outperform larger ones in the long term (Zarowin, 1990). There is a lot of evidence indicating overreaction and the adoption of contrarian strategies by various researchers. However, there is currently a lack of recent

studies comprehensively examining the entire US market, including the impacts of the latest events. The question arises: if we employ a contrarian strategy ourselves, can the excess return or alpha be generated and can such outcomes be explained by the market factors? Through this thesis, I am to investigate and ascertain whether overreactions are prevalent in the US market during the period spanning from 1980 to 2022, using double sorting for creating contrarian investment portfolios. The study will extend its analysis across the entire spectrum of US stocks, ranging from nano to mega caps.

Moreover, this research seeks to assess the effectiveness of implementing a contrarian strategy with the goal of generating profits in the presence of overreaction by the regular investor:

**Research Question:** can a regular investor profit from the Overreaction Hypothesis if risk, liquidity and size also have been accounted for?

We will employ characteristics to adjust our returns based on the recently published Global Factor Data shared by Jensen, Kelly, and Pedersen (2022). In the next sections we will delve into the literature, summarizing those characteristics.

## 2 Literature

### 2.1 Mean Reversion in the Markets

In the context of the contrarian investment strategy based on reversal of the asset price, the important factor is that the markets show mean reverting behavior, as this strategy involves investing in former loser stocks and engaging in short sales of former winners in different time frames. Mean reversion is a widely employed concept in asset investing which is grounded in the empirical observations that both high and low prices of an asset are of temporary nature. It assumes that the stock prices tend to converge toward an average over time making this an important aspect in investment decision making and creating portfolio strategies. More in depth when the current price of a stock falls below the average price, this stock will become attractive for the investors in terms of purchasing, it is to be expected to move back to the average after this event. Conversely, if the price of a stock is above the average the expectation is influenced by the anticipation of mean reversion. The underlying intuition of this event is the impact of firms' performance on the market movements. As higher returns are realized, more competitors are attracted, resulting in a reduction of the firm's market share and subsequent lower returns. Conversely, if the market is saturated with competitors, this may lead to the exit of various firms, creating the possibility for the remaining companies to increase their market share and returns.

### 2.2 Short Term Reversal

Fama (1998) found that the prices are unpredictable due to a random walk, implying market efficiency. Consequently, overreaction and underreaction with long-term returns disappear. Various studies on this topic, including one by Poterba and Summers (1988), discovered mean reversion in the short term on the US markets but not in the long run. Thus, it appears they were unable to dismiss the random walk theory for the long run as well. The founding fathers of the Overreaction Hypothesis were De Bond and Thaler (1985). They found that investing in previous losers resulted in the outperformance of previous winners by roughly 25% over a time period of three years. One contributing factor identified is the size-effect, where smaller firms, categorized as losers, tend to outperform their larger counterparts, yielding higher abnormal returns. This insight has

been investigated and confirmed by Zarowin (1990) and Chopra et al. (1992). However, these later investigations introduced size-adjustment, resulting in relatively lower abnormal returns for the losers mentioned before. Short-term overreaction is also been proven by Lo and McKinlay (1990), where abnormal returns are achieved through weekly or monthly stock picking. A recent study by Piccolo and Chaudhury (2018) also found evidence supporting the Overreaction Hypothesis. However, it missed adjusting for abnormal returns against transaction cost as well as accounting for liquidity in the form of trading volume. The differences in the return and overreaction can also be attributed to an important variable, which is a calendar anomaly that could explain the Overreaction Hypothesis investigated by Rozeff and Kinney (1976). They found the highest abnormal returns to be present in January compared to any other months of the year. The main driver of this phenomenon is believed to be the selling pressure as consequence of the portfolio rebalancing at the end of the year.

### 2.3 Long Term Reversal

Most studies mentioned earlier demonstrate short-term overreaction. Clare and Thomas (1995) stated that the reversal in returns reflect changes in equilibrium of required returns. This view has been shared by other researchers like Ball and Kothari (1989) and Chopra et al. (1992). In the literature, small differences in stock returns between winners and losers are observed. Chan (1988) pointed out that maintaining the same beta for losers and winners over time is inaccurate when calculating the abnormal returns. This idea has been supported by Jones (1988). He showed that the contrarian strategy criteria depend on the market performance during the formation period, essentially stating that the abnormal return gains can be attributed to differences in risk rather than exploiting market overreactions. The Equity value is being influenced by betas, resulting in changes of the Debt to Equity (D/E) ratio, which, in turn, lead to changes in return and risk. An increasing stock price will result in a decrease in leverage and a corresponding decline in risk. Additionally, overreaction has been linked to behavioral biases, including cognitive biases and herding behavior, as suggested by Piccolo and Chaudhury (2018). Physiological factors, such as investor sentiment and market emotions, have also been shown to influence overreaction dynamics. Overall, empirical evidence supports the

existence of overreaction in financial markets. The interaction between overreaction and other market anomalies underscores the complexity of investor behavior.

Furthermore, short term and long term reversal strategies appear to be effective across multiple asset classes, as demonstrated by Zaremba et.al (2019) and Kelly et al. (2021). However the formation periods and strategies to maximize the profits differ among asset classes and certain periods of time (Cheema, 2013).

In our research, we will focus on using the Overreaction Hypothesis to develop our own contrarian strategy, specifically focusing on short term reversal, utilizing stocks from the entire US market. This approach will incorporate a fresh perspective by integrating portfolio formations and employing characteristics to adjust for liquidity, size, P/E ratio and risk factors.

## 2.4 Contrarian Strategies and Reversal Return

Lo and McKinlay (1990) have contributed by documenting the presence of return reversals at a monthly interval. The culmination of these investigations suggests that contrarian strategies, which involve strategically selecting stocks based on their prior week or month returns, can yield abnormal returns. Also stating that a substantial portion of abnormal returns can be attributed to the delayed response of a stock's price to conventional factors, rather than driven by an overreaction in the market. Lehmann (1990) found return reversals on a weekly basis. Other researchers provide data suggesting that the short-term reversals manifest after adjusting the computed returns for size and risk measures. Additionally, equally important studies delve into transaction volume as a significant variable influencing stock price movement. In the case of short-term reversals, there is a correlation with high transaction volume, as opposed to low transaction volume, as observed in the study done by Conrad, Hameed and Niden (1994). The interpretation of why the reversal strategies have superior returns is still a source of controversy despite the facts of their effectiveness from the research literature. The rationale behind these strategies generating higher returns is that they are employed against an opposing pool of investors, who, in turn, utilize different approaches with their own biases, such as extrapolating past earnings into the future or overreacting to negative or positive news. It's said that a well performing stock historically will be favored which in turn will create inflation of the growth stocks. Contrarian investors avoid this trap by

investing in undervalued stocks thus losers and selling the overvalued ones thus winners over a period of time. Contrarian strategies have exhibited outperformance, as demonstrated by De Bondt and Thaler (1985) and Haugen (1994). The evidence suggests that returns are realized in the long run, with a holding period of 3 to 5 years. Fama and French (1992) have argued that contrarian strategies, including portfolios comprising a high proportion of stocks with high Book Equity to Market Equity ratio, inherently bear more risk. This should explain the behavior of the returns as simply a risk premium.

## 2.5 Price to Earnings (P/E) and (E/P)

In the research studies, we frequently encounter the multiple known as price to earnings ratio (P/E), which often has been utilized to test its effect on the stock returns. It is a financial metric that compares the company's current stock price to its earnings per share, which in turn indicates how much investors are willing to pay for each dollar of earnings. A high P/E ratio will typically indicate a growth stock with a lot of potential (Graham and Dodd, 1934). Their research in security analysis introduced P/E ratio or Earnings to price (E/P). E/P ratio, in turn, signifies how much is being earned for each dollar invested. Their results demonstrated a higher returns for the stocks with low P/E ratios compared to the stocks with the high P/E ratios and vice versa for E/P ratios. The concept of E/P ratio became prominent in later studies, and in recent years, it is being used as a complementary metric in the valuations. Asness, Moskowitz and Pederson (2013) examined the performance of value and momentum across global equity markets, utilizing E/P ratio as a value factor to explain the stock returns. (Hou, Xue and Zhang, 2015) investigated the performance of various anomalies found in the stock markets, exploring E/P ratio as a contributing factor to these anomalies and its utilization in the value investment strategies. Jaffe, Keim and Westerfield (1989) studied the effect of E/P ratio and size on stock returns.

Given the historical significance and relevance of E/P ratio in stock valuation, as well as contrasting performance observed in prior studies between stocks with low and high E/P ratios, our study aims to test the hypothesis that the E/P ratio serves as a significant factor influencing stock returns. Specifically, we anticipate that stocks with low E/P ratios, indicating higher earnings relative to price, will exhibit higher returns compared to stocks with high E/P ratios. This hypothesis aligns with the value investing principle, that

suggests stocks with lower valuation metrics may outperform those with higher valuations. To test this, we will analyze the relationship between the E/P ratio and stock returns of entire US market, contributing of broader understanding of factors influencing the stock returns and effectiveness of contrarian strategies.

## 2.6 Book Equity to Market Equity

This characteristic is no stranger to academic literature; various researchers have conducted studies using Book Equity to Market Equity (BE/ME) for prediction of the stock returns. Numerous studies on this topic have been carried out in the US. The Book Equity to Market Equity ratio is a financial metric that compares the book value to the market value of the company. It is calculated by dividing the book value per share by the market price per share, providing data on the market values a company against its accounting value. A high BE/ME ratio suggests that the market values the company lower than its value in the books, indicating that the company could be undervalued, thereby leading to the contrarian strategy opportunities. Firms with  $ME > BE$  are expected to be priced lower and thus can be sold short, where firms with  $BE > ME$  are expected to be priced higher, similar to the Loser and Winner scenario. Basu (1977) laid the foundation for the research and use of BE/ME, with his study focusing more on the previous section-P/E ratio. Nevertheless he made evident that the stocks with a low BE/ME ratio tended to outperform stocks with a higher BE/ME ratio. Chan, Hamao and Lakonishok (1991) extended their study to broader markets, investigating the Japanese markets, where the results showed the stocks with high BE/ME ratio outperforming the stocks with lower BE/ME ratio. Additionally, Rosenberg, Reid and Lanstein (1985) were able to beat the market using strategies based on BE/ME ratio, adding to the market theory that Efficient Market Hypothesis does not always hold, and the price does not fully represent all the market information. Fama and French (1995) conducted a study of the stock behavior in relation to BE/ME ratio and size, finding that, in long-term, low BE/ME stocks outperform high BE/ME stocks. More recent studies believe that the results achieved are due to an overreaction of the investors and mispricing of the equity part of the equation (Skinner and Sloan, 2002). However, some dismiss overreaction altogether, showing evidence that stock prices are driven by biased behavior of investors in anticipation of future earnings growth, being overly optimistic (DeChow and Sloan, 1997).

By using the double sorting procedure we will try to find out if the stocks with low BE/ME ratio, which indicates in the US that the company is overvalued according to market prices relative to their book values, will exhibit higher returns when the contrarian portfolio formation strategy will be based on this ratio. Will the formation portfolio with Low BE/ME outperform the formation portfolio with High BE/ME? The expectation is that the market does not fully reflect all the available information, so the stocks with high BE/ME ratios may outperform over the short term.

## 2.7 Amihud Measure

Introduction of Amihud measure in the research has made significant contributions to understanding the impact of liquidity on asset pricing (Amihud, 2002). Insights into market dynamics and liquidity show that less liquid stocks tend to have higher expected returns. When examining contrarian strategies, investors often focus on underperformance in short term, expecting mean reversion of performance. Illiquid stocks marked with wider bid and ask spread and higher trading cost could be more attractive in the contrarian framework if mean reversion takes place (Amihud and Mendelsen, 1986). This pioneering work has inspired further exploration and confirmation of the positive correlation between illiquidity and stock returns by researchers such as Eleswarapu (1997), Jacoby et al. (2000) and Gottesman and Jacoby (2006). Lakonishik et al. (1994) examined the illiquidity factor for value portfolios as well as growth portfolios. Gottesman, Jacoby and Li (2017) found a substantial discrepancy between the liquidity of value portfolios and growth portfolios, the value portfolios had higher illiquidity than growth portfolios and elevated returns were observed for value portfolios. This return out of the contrarian strategy was concluded to be a compensation of inherent illiquidity for value portfolios. Also they found a positive relationship of high BE/ME ratio and the illiquidity measure. Will the role of illiquidity effect in our thesis display a superior return by using double sorting method for construction of value ( loser) and growth ( winner ) portfolios?

Given the established relationship between illiquidity and stock returns, incorporating the Amihud measure as a proxy for illiquidity in a double sorting method will enhance the effectiveness of a contrarian strategy. The Overreaction Hypothesis posits that portfolios formed with stocks exhibiting higher illiquidity characteristics will demonstrate stronger

mean reversion. Accounting for inherent illiquidity, the contrarian strategy is anticipated to yield superior returns for Loser portfolios compared to the Winner portfolios. We expect to observe a positive relationship, indicating that portfolios with higher BE/ME ratios are also more illiquid. The findings in our study are anticipated to align with prior research, which has demonstrated the compensation of inherent illiquidity for the Loser portfolios and a positive relation between the BE/ME ratio and the Amihud metric.

## 3 Data

In the thesis, we will investigate the Overreaction Hypothesis using the double sorting procedure of Fama and French (1993). This procedure is based on the Size effect, where the firms are split into five groups based on their Market Capitalization; the Liquidity effect, where firms are split into five groups based on their ranking using Amihud (2002) - a measure of illiquidity by the ratio of absolute stock return to its dollar volume; and the Volatility effect using standard deviation of the returns and E/P ratio groups. Our universe of securities consists of the entire US stock market from January 1980 to December 2022 sourced from WRDS - CRSP database.

In the literature section, we previously examined studies on the Overreaction Hypothesis, the use of contrarian investment strategies and the explanatory variables. With this empirical study we aim to contribute to the research field on contrarian investment strategies, assessing whether the Overreaction Hypothesis still holds when using a large data-set that includes market fluctuation due to major world events like Covid-19 and the War in Ukraine. In the next section, characteristics used in this research will be explained.

### 3.1 Characteristics

The Jensen, Kelly, and Pedersen (2022) Global Factor data is employed in this thesis, encompassing 406 characteristics and their corresponding factor portfolios. This dataset serves as the superset of the 153 factors analyzed in Jensen, Kelly, and Pedersen (2021). To avoid look-ahead bias, firm characteristics are properly lagged relative to stock returns. The following section will explain the market based characteristics we utilized in this thesis:

**Company Market Equity** (me\_company): this company market equity data has been extracted from CRSP and is constructed as the sum of the Market Equity's grouped by unique permanent identifier assigned by CRSP to all companies with issues on a CRSP file - PERMCO.

**Monthly Return Variable** (ret): this CRSP variable is the change in the total value of the investment in a common stock over a defined period of time per unit investment, in this thesis we use 1 month holding period.

**Excess Return** (ret\_exc): {ret-T30RET}; this is a total stock return measured over calendar month (ret) minus 30 day Treasury bill (T30RET); if the T30RET is unavailable the risk-free return rate or One Month Treasury Bill Rate (RF) is being used.

**Book Equity** (be): to the Shareholders Equity (SEQ) the deferred Taxes and Investment Credit (TXDICT) are being added and preferred stock (PSTK) is being subtracted and the values TXDICT and PSTK are set to zero if missing.

**Market Equity** (me): the market equity for the primary stock of the firm is being used, the market value is not aligned with the end of the fiscal period. The market value is being updated on the monthly basis and aligned to the most recently available accounting characteristics.

**Book Equity to Market Equity** (be\_me): is a ratio between the Book Equity and Market Equity on a monthly basis.

**Net Income** (ni): net earnings when not available, the following is being used - earnings before Tax and Extraordinary (PI) Items subtracted by Income Tax (TXT) and Noncontrolling Interest (MII)

**Net Income to Market equity** (ne\_me): E/P ratio; NI divided by ME on monthly basis.

**Cumulative Return** (ri): for this variable the cumulative return is being derived from ret.

**Dollar Volume** (dolvol): this uses trading volume(TVOL) scaled by price (PRC).

**Amihud 126 Day Measure** (ami\_126d): This measure is computed as the average of the absolute value of daily return (ri) divided by the dollar volume (dolvol) over 126 days scaled by 1 million.

**Realized Return Volatility 252 Day Measure** (rvol\_252d): this is computed by using standard deviation of daily excess returns over 252 trading days.

**Total Return Past (N) Days** (lbk\_5day);(lbk\_10day);(lbk\_20day): using daily data we compute total return over previous 5;10;20 day period per company id on monthly basis.

**Size Grouping** (size\_grp): groups of Mega cap (80<sup>th</sup> percentile of NYSE), Large cap (remaining stocks above the 50<sup>th</sup> percentile), small cap (above 20<sup>th</sup> percentile), micro-cap (above 1<sup>st</sup> percentile) and nano cap (remaining stocks) are being formed. There is no overlapping and the breakpoints are based on the market equity of NYSE by the end of each month. The NYSE breakpoints are provided by the Jensen, Kelly, and Pedersen (2022) Global Factor Data.

The next section will describe these descriptives with focus on checking the dataset.

### 3.2 Descriptive statistics

In the upcoming section, the descriptive statistics for the characteristics utilized in this thesis will be presented.

**Table 1 :Descriptive Statistics**

Statistics and Percentiles of firm variables are computed over all firms and the full sample. The descriptive statistics for firms are computed per time period. Data sample runs from 1980-01-31 to 2022-12-31 on a monthly frequency; Market Equity of PERMCO is measure in millions USD.

Characteristic	Variable	Mean	Std. Dev	5%	25%	50%	75%	95%	Skewness	Kurtosis
Firms	<b>firms</b>	5,545	1,112	4,127	4,447	5,320	6,248	7,671	0.4	-0.9
Market Equity of PERMCO	<b>me_company</b>	2,565	20,562	4	27	124	689	8,325	48	4,016
Monthly Return	<b>ret</b>	1.0%	18.2%	-23.8%	-7.0%	0.0%	7.2%	27.5%	265.2%	3003.8%
Monthly Excess Return	<b>ret_exc</b>	0.6%	18.2%	-24.4%	-7.4%	-0.4%	6.9%	27.1%	265.0%	3001.7%
Book Equity to Market	<b>be_me</b>	0.82	1.22	0.08	0.30	0.57	0.98	2.17	14.07	436.99
Net Income to Market	<b>ni_me</b>	-0.13	1.33	-0.66	-0.04	0.04	0.07	0.16	-29.03	1433.05
Amihud 126 Day Measure	<b>ami_126d</b>	7.91	58.38	0.00	0.01	0.09	1.44	26.71	29.84	1569.73
Realized Volatility 252 Day Measure	<b>rvol_252d</b>	3.7%	2.6%	1.3%	2.0%	3.0%	4.6%	8.5%	289.4%	1660.3%
Total Return Past 5 Days	<b>lbk_5day</b>	0.3%	8.9%	-11.9%	-3.3%	0.0%	3.2%	13.1%	204.6%	2427.1%
Total Return Past 10 Days	<b>lbk_10day</b>	0.2%	12.4%	-16.8%	-4.9%	0.0%	4.4%	18.2%	208.4%	2324.6%
Total Return Past 20 Days	<b>lbk_20day</b>	0.8%	17.7%	-23.4%	-7.0%	0.0%	7.0%	26.7%	260.4%	2995.9%

In Table 1 Market Equity of the firm in the dataset consists of the mean of 2.6 billion and a standard deviation of 20.6 billion, with the 5<sup>th</sup> percentile at 4 million market equity and the 95<sup>th</sup> percentile equal to 8.3 billion market equity. This implies that the market value of the firms is not normally distributed as one standard deviation suggests a Market Equity beyond the 95<sup>th</sup> percentile. The Skewness and Kurtosis of all characteristics indicate a highly skewed and leptokurtic distribution. This indicates that most firms in our dataset have positive characteristics that are peaked around their mean, except for Net Income to Market Equity characteristic. This, in turn, gives the rationale for investigating size-adjusted loser winner reversal strategy, given the dataset's prevalence of smaller firms compared to larger ones. The Average Monthly Returns over the entire dataset are 1%, with a standard deviation of 18.2%. The return distribution spans from 95<sup>th</sup> percentile returns of 27.1% to the 5<sup>th</sup> percentile returns of -23.8%. Assuming a normal distribution with a 1% Average Monthly Return and standard deviation of 18.2% we would expect 13.3% return at 75<sup>th</sup> percentile. However, we observe a return that is on average 1.84 times smaller. The Excess Monthly Return yields almost the same values as the Monthly Return, with the difference in average return between the two being 0.4% (risk-free rate). Book Equity to Market has mean value of 0.82 and standard deviation of 1.22, with the 95<sup>th</sup> percentile at 2.17. Assuming that a Book to Market ratio of 1 represents a fairly valued firm, our dataset appears to consist mostly of undervalued stocks. Notably, at the 75<sup>th</sup> percentile, the Book to Market ratio is 0.98. This dataset will be adjusted by this characteristic in our thesis. A negative Average Net Income to Market ratio (Earnings to Price) of -0.13 is observed, which cannot be interpreted for the valuation of a company since we cannot repurchase a company with negative earnings. Overall, our dataset consists of a low positive Net Income to Market ratio. At the 50<sup>th</sup> percentile, the dataset consists of a positive Net Income to Market ratio of 0.04 and above, representing half of the companies in the dataset. Therefore, the median (i.e., 0.50 percentile) and mean exhibit radical differences, with 0.04 and -0.13, respectively. This highlights the sensitivity of the mean, which needs to be taken into account. High values of the Amihud ratio imply lower liquidity because the price change is relatively high compared to the dollar volume. We observe a mean of 7.91 and a standard deviation of 58.38, with an Amihud ratio of 1.44 at the 75<sup>th</sup> percentile. This can be explained by containment of significant amount of micro and nano companies in the dataset that is why size grouping will be applied. Daily Volatility is high with mean of 3.7% on a daily basis, which is expected due to the large

number of micro and macro caps in the dataset. The distribution of Lookback Returns by construction is logical; as the number of the lookback days increases, the values of standard deviation and their mean also increase.

**Tabel 2: Descriptive Statistics by Size groups**

Averages by Size grouping over the dataset period 1980-01-31 to 2022-12-31. Market Equity is measured in millions. we use size groupings provided by Jensen, Kelly, and Pedersen (2022) Global Factor Data: Mega cap (80th percentile of NYSE), Large cap (remaining stocks above the 50th percentile), small cap (above 20th percentile), micro-cap (above 1st percentile) and nano cap (remaining stocks).

Variable	Mega	Large	Small	Micro	Nano
<b>firms</b>	373	691	1,138	2,385	949
<b>me_company</b>	30,173	3,102	735	131	15
<b>ret</b>	1.74%	1.94%	1.93%	1.24%	-1.44%
<b>ret_exc</b>	1.45%	1.63%	1.61%	0.89%	-1.84%
<b>be_me</b>	0.510	0.564	0.620	0.825	1.383
<b>ni_me</b>	0.054	0.041	0.018	-0.089	-0.617
<b>ami_126d</b>	0.002	0.031	0.219	5.402	42.107
<b>rvol_252d</b>	2.01%	2.39%	2.96%	4.06%	6.48%
<b>lbk_5day</b>	0.48%	0.55%	0.53%	0.27%	-0.43%
<b>lbk_10day</b>	0.72%	0.76%	0.68%	0.30%	-1.06%
<b>lbk_20day</b>	1.63%	1.73%	1.69%	0.98%	-1.52%

**Figure 1: Average Firm Count over Time per Size Group**

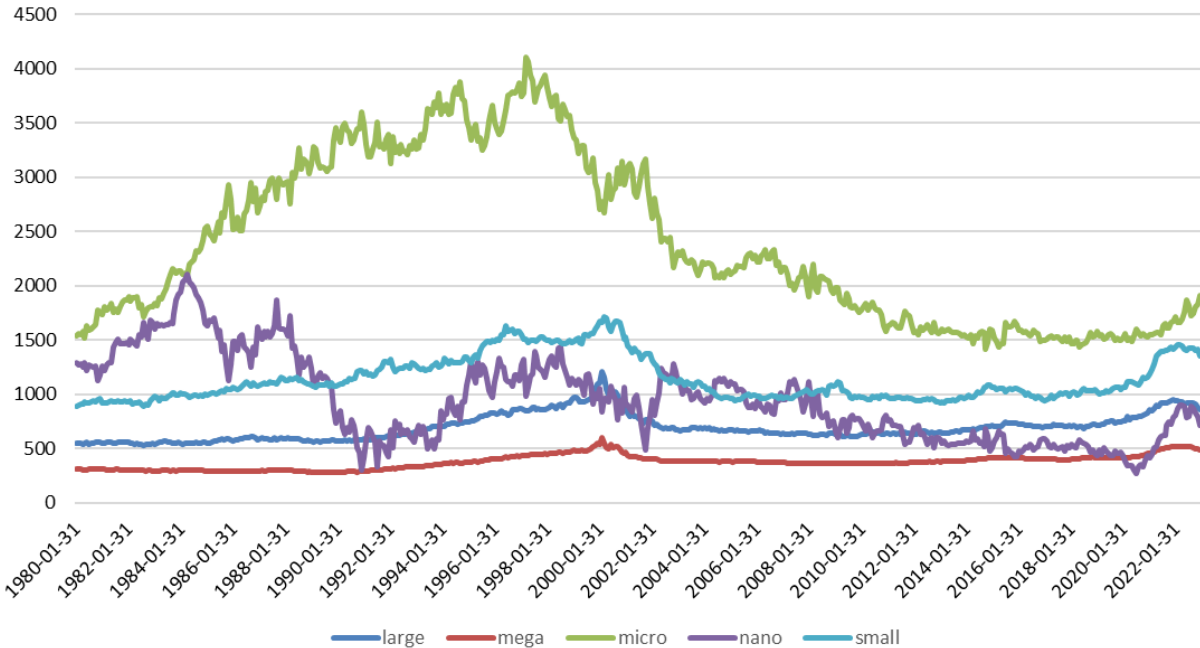


Table 2 illustrates the size grouping aspect applied to our dataset using Global Factor Data. On average, every month, the number of firms ranges from 373 mega to 949 nano stocks. We observe a market equity of 30 billion for the mega caps on average and 15 million for the smallest group. The small, micro and nano firms from Table 2 collectively represent roughly 80% of the sample, suggesting that our results may be influenced by small firm sizes. This motivates us to investigate the overreaction hypothesis within each size group separately. Book equity to Market equity ratio increases across the groups, being highest for nano stocks 1.384. This implies that nano stocks may be undervalued, as the average book value of the stocks is higher than the market value. In contrast, for the mega caps and large caps, the ratios are 0.510 and 0.564, respectively. Returns tend to be negative for the nano category, even though they are undervalued, while positive returns are displayed for small and micro caps. Net income to Market Equity for mega caps, with value of 0.054, equals a P/E multiple of 18.5 times its average annual earnings. For large and small caps, the P/E multiples are 24.4 and 55.6, respectively, indicating a higher valuation for lower capitalized firms on average. However, for micro and nano firms, negative earnings to price ratios are observed, possible explanations could be an unprofitable business model, nearly bankrupt firms with a high turnover and delisting. The Amihud illiquidity measure has relatively low values of 0.002, 0.031, 0.219 for mega caps, large caps and small caps, respectively. This increases significantly for micro and nano, indicating very low liquidity and implying high transaction costs. Return volatility increases on average with lower firm size. Mega caps have an average daily (measured over 252 trading days) volatility of 2.01%, while large and small firms have a daily volatilities of 2.39% and 2.96%. Micro and nano sized firms have even higher daily volatilities of 4.06% and 6.48%, respectively. The average lookback returns increase with the lookback period. Mega caps' average lookback return is 0.42% to 1.63% for the lookback periods 5 to 20 days, respectively. Positive lookback returns can be observed for all groups except for nano caps, which show negative 5 to 20 day average returns of -0.43% to -1.52%.

### **Average per Firm characteristic per decade**

As illustrated in Table 3, Market Equity over the time-span from 1980 to 2020 (the period before Covid-19) experienced a major increase, rising from an average 284 million on average to 7 billion. This marks a substantial increase of 2606%, with returns declining

substantially per decade. In 1980, the overall US market was able to achieve an average return of 1.42% and an abnormal return of 0.59%. Compare that to 1990, where the values declined to 0.86% and 0.42% for average return and average abnormal return, respectively. The Book Equity to Market Equity ratio displayed a decline from 1980 to 1990, dropping from 0.948 to 0.831. However, it increased from 2000 to 2010, going from 0.778 to 0.839. In current times, the ratio is 0.76, implying that the market equity increased per decade on average. An increase in illiquidity is observed from 1980 to 1990 and 2000, with Amihud values of 2.680, 14.683 and 8.409, respectively. However, there is a change from 2000 onward, suggesting that the introduction of electronic trading could be a reason for more efficient ways to trade for market participants. On average, the volatility varied over time, with values ranging from 2.86% in 1980 and 3.49% in 2020.

**Tabel 3: Descriptive statistic Average per characteristic per firm over the decades**

Characteristic	1980	1990	2000	2010	2020
<b>me_company</b>	284	558	1,855	3,764	7,687
<b>ret</b>	1.42%	0.86%	1.44%	0.79%	0.44%
<b>ret_exc</b>	0.59%	0.42%	1.12%	0.68%	0.37%
<b>be_me</b>	0.948	0.831	0.778	0.839	0.760
<b>ni_me</b>	0.003	-0.149	-0.149	-0.139	-0.164
<b>ami_126d</b>	2.680	14.683	8.409	6.295	2.767
<b>rvol_252d</b>	2.86%	3.84%	4.24%	3.41%	3.49%

**Book Equity to Market Equity ratio** displays a downward-sloping trend on average over time for five size groupings seen in the chart below. Crisis events are evident; for example, during the period of 2000-2002 ( Dot-Com bubble), there is a decrease in market equity relative to book value. The Financial Crisis of 2008 has a significant impact, as seen in the chart with a spike visible for all five size groups of firms. The Covid-19 spike of the average Book to Market ratio can be observed from 2020 to 2022.

**Figure 2: Average Firm BE\_ME over Time per Size Group**

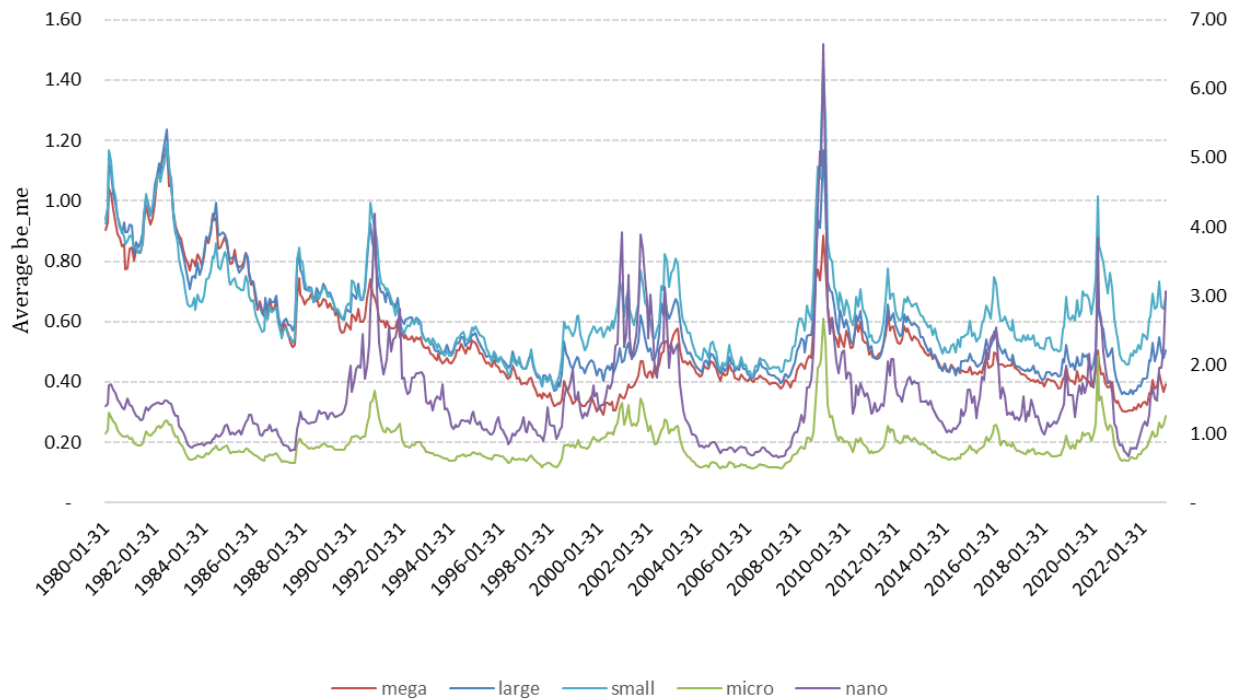


Figure 3 below illustrates the **Average Earnings to Price ratio** for five size groups: mega, large and small. All size groups exhibit downward-sloping average Earnings to Price ratios, and the chart clearly depicts the effects of the crisis events discussed earlier. Negative values appear during the same time periods (2000, 2008, 2020) with a range of 2 to 4 years. This implies that market equity is declining while earnings are negative. In 2000, small caps had average Earnings to Price ratio of approximately -0.055, while mega caps were slightly below zero. The impact of these crisis events on the market equity of smaller firms makes them more risky, as confirmed by our data, with a negative spike during the Financial Crisis, resulting in an average E/P ratio roughly -0.3 for small caps. Even during this crisis, the entire US market seems to be slightly positive overall. Negative Average Earnings to Price ratio during the Covid-19 crisis are also evident for small firms in the range of -0.05. Mega Caps and Large Caps perform better in comparison.

**Figure 3: Average Firm NI\_ME over Time per Size Group**



The Average Amihud Illiquidity measure for all group sizes reveals the highest increase in illiquidity during crisis events, particularly noticeable for the nano, micro and small groups, which are particularly vulnerable. Additionally, it is evident that the level of liquidity increases with the size of the firm. During crisis periods, the rising Amihud level can be explained by higher absolute returns and/or lower dollar trading volume.

**Figure 4: Average Firm AML\_126D over Time per Size Group**

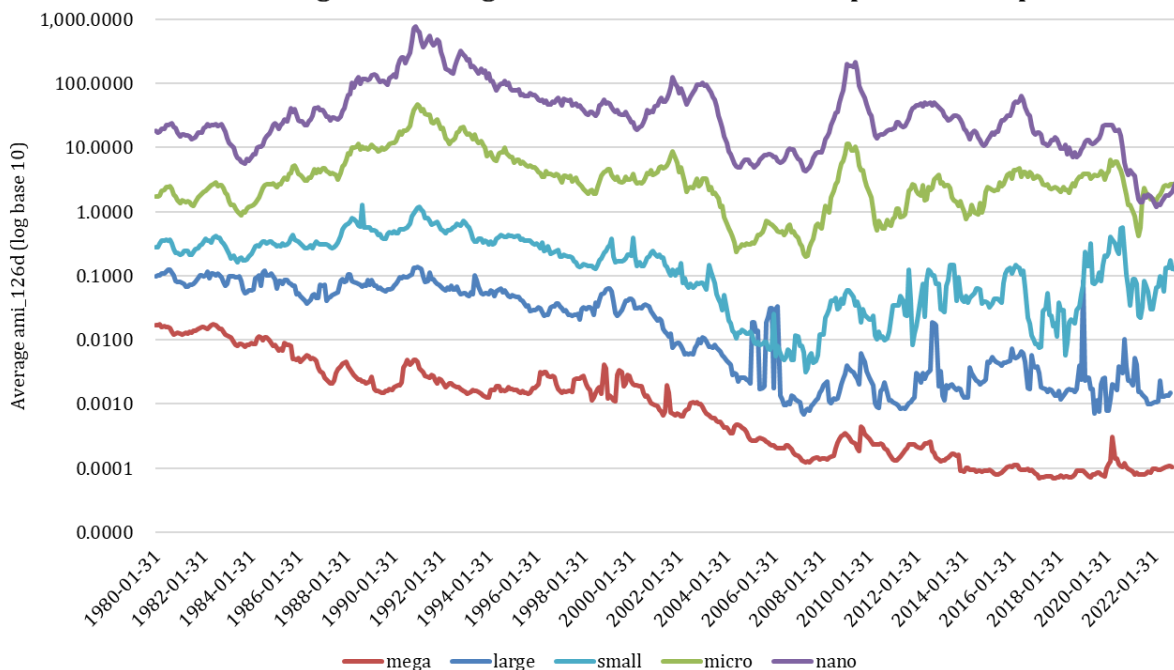
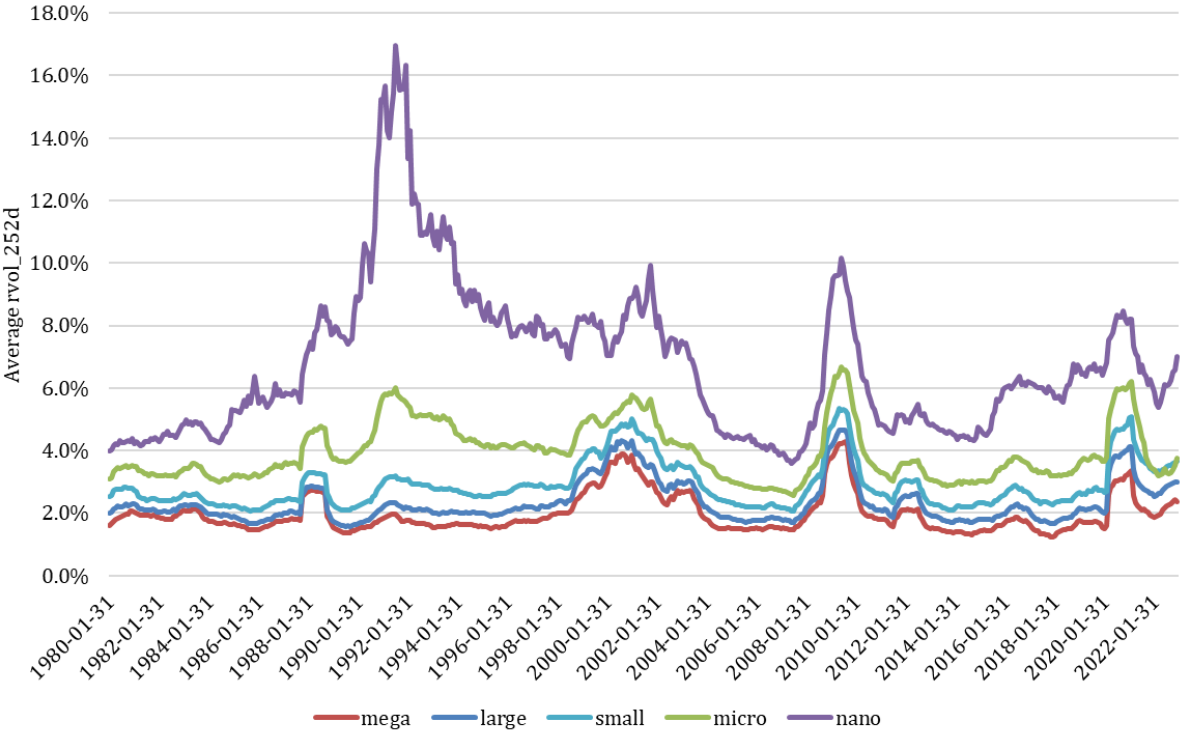


Figure 5 below displays the **Average Firm Volatility** calculated over a 256-day period for all size groups in the dataset from 1980 to 2022. Extreme values can be observed for nano, micro and small caps, with nano exhibiting a peak of roughly above 16% volatility around 1990-1994. This means that in any given month, the return can fluctuate by an average of 16%, which is substantial. Similar patterns apply to micro and small caps. The spikes in the chart below can be explained by historic extreme events in 2000-2002 (Dot Com bubble), 2008-2010 (Financial Crisis), and 2020-2022 (Covid-19), in contrast to the previous charts, there is also a significant impact on average volatility, even for mega caps. During the financial crisis the average return volatility could be as high as 4%, twice as high compared to regular volatility of 2% seen in the figure.

**Figure 5: Average Firm rvol\_252d over Time per Size Group**



## 4 Methodology

### 4.1 Measuring overreaction

Our three proxies for measuring overreaction are the Total Excess Returns over three different historical trading periods, ranging from 20 days to replicate Short-Term Mean Reversion, to 10 and 5 trading days for an even more shorter-term overreaction. For each Month-End and each security, we compute the Total Excess Returns over the previous 5, 10 and 20 trading days, creating three additional characteristics named **lbk\_5day**, **lbk\_10day** and **lbk\_20day**. Based on these characteristics, securities are sorted and assigned to five quintiles ordering from 1 (Loser) to 5 (Winner). Securities assigned to the Loser quintile belong to the 20% of firms with the lowest Total Excess Returns measured over the previous trading period. Conversely, securities assigned to the Winner quintile belong to the 20% of firms with the highest Total Excess Returns measured over the prior trading period. Securities with no data available over the prior trading period are omitted from the assignment, ensuring that these do not influence the end result.

### 4.2 Single Sort Loser – Winner Portfolio Strategy

For each of the five quintiles, we will form portfolios by equally weighting the assigned securities to each quintile, generating five portfolios that are rebalanced on a monthly basis. The portfolio return for each quintile portfolio is computed as the average of Total Excess Return for each assigned security measured over the next month. The portfolio return of the contrarian investment strategy, which is short the Winner portfolio and is long the Loser portfolio, is defined as the return of the Loser portfolio minus the return of the Winner portfolio.

### 4.3 Double Sort Loser – Winner Portfolio Strategy

For our double sorting portfolio formation strategy, we condition the Loser-Winner Portfolio sorting procedure on our set of characteristics: Size (**size\_grp**), Book Equity to Market Equity (**ni\_me**), Net Income to Market, Realized Return Volatility (**rvol\_252d**) and the Amihud Illiquidity ratio (**ami\_126d**). We condition by first sorting securities by the characteristic into five quintiles ordering from High (5) to Low (1). Securities assigned to the High quintile belong to the 20% of firms with the highest characteristic values. For

example, the High quintile based on the Amihud Illiquidity ratio contains the top 20% of securities with the highest illiquidity ratios, thus being notoriously difficult and likely expensive to trade. The reverse argument holds for the Low quintile based on this characteristic.

Then within each characteristic quintile (or size grouping<sup>1</sup>), we apply the single sort procedure using our overreaction proxy, Total Excess Returns measured over the previous 5, 10 and 20 trading days, and again assign these securities to five quintiles, ordering from 1 (Loser) to 5 (Winner). This produces twenty-five separate groupings, which we follow up by forming twenty-five equally weighted portfolios for the double sorted characteristic and selected overreaction proxy. This gives us five independent Loser and five independent Winner portfolios, such that we can form five Loser-Winner portfolios. The return of each portfolio is again simply the average of Excess Returns of assigned securities measured over the next month. The Loser-Winner portfolio return that we investigate is the average of Loser-Winner portfolio returns of these five Loser-Winner portfolios, thus averaged over the five separate characteristic quintiles, such that this final Loser-Winner portfolio does no longer covary with the conditioned characteristic.

#### 4.4 Loser – Winner Return Analysis

The Loser-Winner portfolio returns are likely to be influenced not only by the observed return reversal following a period of overreaction but also by various risk factors. The Capital Asset Pricing Model (CAPM) model states the average excess return of any portfolio or security is linearly related to the market excess return (Market Risk Factor) by the size and sign of the CAPM Beta. While this model is simple, it fails empirically for portfolios and stocks with strong tilts to Size and Valuation (High Book to Price) in explaining their average excess returns. To address this, Fama and French (1993, 1995) introduced the Size and Value Risk factors, which significantly increased the explanatory power of the model when applied to portfolios and stocks with varying characteristics. In addition to the Size and Value Risk factors, the Fama-French Five Factor Model (Fama and French, 2015) expands by including the Profitability factor and the Investment Risk

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<sup>1</sup> The Size characteristic is an ordinal scale as it based off the firm Market Equity, the assignment of labels is determined by the NYSE breakpoints mentioned earlier, see Jensen, Kelly, and Pedersen (2022).

factors. Empirical observations suggest that these factors are important in explaining the excess returns of portfolios and stocks with strong tilts to such characteristics.

The Momentum factor, introduced by Jegadeesh and Titman (1993), is typically adjusted for the 1 Month reversal period to acknowledge its impact on short – term market dynamics. The Momentum factor is then typically added to the Fama French models to provide a more comprehensive explanation of excess stock returns.

In this study, we will investigate the excess stock returns of the Loser-Winner portfolios using the Fama-French Five Factor Model with the Momentum as an additional factor. This addition aims to provide a more nuanced perspective on the Loser – Winner portfolio returns. The goal is to isolate the excess returns of the contrarian strategy due to reversion from these well-known and widely acknowledged risk factors. If there is any significant alpha left, we can be confident that the remaining average excess return, or alpha, is due to the reversion anomaly.

The appendix contains a more extensive overview of the different factor models, explaining each factor, and includes their model specifications. For this thesis, the Factor Models are estimated using Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors to account for autocorrelation and heteroskedasticity present in the residuals, to provide robust inference and is standard practice. The time series of factor returns data is sourced from Kenneth French's data library website.

## 5 Results

### 5.1 Loser – Winner Portfolio Returns

In this section, we will employ single sorting to generate Loser and Winner portfolios across three distinct lookback periods. Our objective is to investigate whether reversion is evident and whether excess returns are present, in line with the Overreaction Hypothesis, utilizing our contrarian investment strategy.

**Table 4: Portfolio Returns of Loser and Winner portfolios for single sorts**

In this table we report the average Portfolio Returns of Equal Weighted Portfolios. Reported statistics are on a monthly frequency. Portfolios are formed by sorting securities on their total excess return over the past 5, 10 or 20 trading days. Five quintile portfolios are created every period, the Loser portfolio consists of those securities with the lowest 20% excess returns, the Winner portfolio consists of securities with the highest 20% returns over the relevant lookback period. Portfolios are formed on monthly basis, there are 515 months in our sample, which runs from January 1980 to December 2022. The normal distribution is assumed in computing the P-values.

<b>Panel A</b>	<b>Statistic</b>	<b>Loser</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>Winner</b>	<b>Loser-Winner</b>
5 Day	Mean	0.79%	0.76%	0.75%	0.79%	0.25%	0.54%
	Std	7.89%	5.69%	4.93%	5.03%	6.40%	3.46%
	Sharpe	0.10	0.13	0.15	0.16	0.04	0.16
	Months	515	515	515	515	515	515
	T-Statistic	2.28	3.05	3.47	3.57	0.88	3.57
	P-value	1.13%	0.12%	0.03%	0.02%	18.86%	0.02%
<b>Panel B</b>	<b>Statistic</b>	<b>Loser</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>Winner</b>	<b>Loser-Winner</b>
10 Day	Mean	0.76%	0.73%	0.79%	0.79%	0.27%	0.48%
	Std	8.14%	5.73%	4.93%	4.98%	6.38%	4.55%
	Sharpe	0.09	0.13	0.16	0.16	0.04	0.11
	Months	515	515	515	515	515	515
	T-Statistic	2.11	2.87	3.64	3.61	0.97	2.41
	P-value	1.73%	0.20%	0.01%	0.02%	16.49%	0.79%
<b>Panel C</b>	<b>Statistic</b>	<b>Loser</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>Winner</b>	<b>Loser-Winner</b>
20 Day	Mean	0.63%	0.62%	0.84%	0.82%	0.41%	0.22%
	Std	8.40%	5.77%	4.87%	4.94%	6.24%	5.09%
	Sharpe	0.07	0.11	0.17	0.17	0.07	0.04
	Months	515	515	515	515	515	515
	T-Statistic	1.70	2.44	3.92	3.77	1.48	0.99
	P-value	4.44%	0.73%	0.00%	0.01%	6.95%	16.01%

In **Table 4** above, we report the results for constructed portfolios that are split into five quantiles, with the top 20% as the Winner quantile and lowest 20% as the Loser quintile. In Panel A, with 5-day lookback period, we observed a mean excess return on a monthly basis for the Loser portfolio over the span of the whole dataset of 0.79%, compared to 0.25% for the Winner portfolio. The difference between the two consists of a 0.54% excess

return on a monthly basis. For the 5-day lookback period, the results are supportive of the Overreaction Hypothesis and the contrarian strategy, indicating that it will deliver profits at first glance. A high t-value of 3.57 can be observed for the contrarian Loser-Winner strategy, yielding a positive average and a significant reversion return. The Sharpe ratio for the Loser and Winner quintile is the lowest out of all quintiles. This holds for all three lookback periods, it appears that the standard deviation is also the highest for the Loser and Winner quintile portfolios. The Loser-Winner contrarian strategy is only significant for the 10 Day and 5 Day lookback periods. The average returns of the quintile portfolio do not follow a monotonic pattern in average excess returns. Instead, we see equal returns on average from the Loser quintile up to quintile 4. The Winner quintile portfolio experiences a large decrease in average returns, resulting in a “cliff”-like pattern of average returns. Standard deviation for the Loser portfolio is higher with a value of 7.89 compared to a value of 6.40 for the Winner portfolio, suggesting that there’re less risky firms in the higher 20<sup>th</sup> quantile. If we increase the lookback period from 5 to 10 days in Panel B, the overreaction is still being observed, with Loser quintile portfolio showing almost the same values as for the 5-day lookback period, with a mean excess return of 0.76% versus 0.27% for the Winner quintile portfolio. There is a slight decrease in the excess return from 0.54% of the 5-day lookback period to 0.48%, so there is short-term reversion which is still present and our contrarian strategy is profitable. In the next panel (Panel C), we increase the lookback period by an additional 10 days, making it in total of 20 days. The reversion effect is still present, with the mean returns of the Loser quintile portfolio at 0.63% versus the Winner quintile portfolio at 0.41%. The returns are decreasing, with the Winner minus Loser excess returns being 0.22% for the 20-day lookback period compared to 0.54% for the 5-day lookback period. We find the lookback period of 5-Days to be optimal in terms of Sharpe ratio, with it being four times higher compared to the 20-Day lookback period and 50% higher compared to the 10-Day lookback period.

## 5.2 Characteristics of Loser-Winner Portfolios

In the previous section, we investigated simple contrarian strategy without adjusting for tilts towards firm characteristics. Single portfolio sorts is a crude method, thus we expect that sorting for overreaction is likely to proxy for other characteristics. By construction Winners will have higher market equity relative to Losers, this introduces a valuation effect. Additionally, Winners and Losers are likely to exhibit higher risk due to overreaction. This section investigates this hypothesis and will help us understand whether any tilts are present.

**Table 5: Portfolio Characteristics of Loser and Winner portfolios for single sorts**

In this table we report the average Portfolio Characteristics of Equal Weighted Portfolios. Portfolios are formed by sorting securities on their total excess return over the past 5, 10 or 20 trading days. Five quintile portfolios are created every period, the Loser portfolio consists of those securities with the lowest 20% excess returns, the Winner portfolio consists of securities with the highest 20% returns over the relevant lookback period. Portfolios are formed on monthly basis, there are 515 months in our sample, which runs from January 1980 to December 2022. The normal distribution is assumed in computing the P-values.

<b>Panel A</b>	<b>Quintile</b>	<b>me_company</b>	<b>ret_exc_lead1m</b>	<b>be_me</b>	<b>ni_me</b>	<b>ami_126d</b>	<b>rvol_252d</b>	<b>5 Day</b>	<b>10 Day</b>	<b>20 Day</b>
5 Day	Loser	1,279	0.79%	0.98	-0.32	13.2	4.9%	-9.4%	-8.4%	-7.7%
	2	3,129	0.76%	0.78	-0.05	4.7	3.3%	-2.5%	-2.3%	-1.6%
	3	3,736	0.75%	0.77	-0.04	5.6	3.1%	-0.1%	-0.1%	0.6%
	4	3,583	0.79%	0.73	-0.02	4.2	3.1%	2.4%	2.2%	2.9%
	Winner	1,823	0.25%	0.78	-0.17	11.4	4.4%	10.9%	10.0%	10.4%
<b>Panel B</b>	<b>Quintile</b>	<b>me_company</b>	<b>ret_exc_lead1m</b>	<b>be_me</b>	<b>ni_me</b>	<b>ami_126d</b>	<b>rvol_252d</b>	<b>5 Day</b>	<b>10 Day</b>	<b>20 Day</b>
10 Day	Loser	1,191	0.76%	1.02	-0.35	13.3	4.9%	-6.4%	-13.1%	-11.6%
	2	2,967	0.73%	0.80	-0.05	5.2	3.4%	-1.6%	-3.8%	-3.0%
	3	3,658	0.79%	0.78	-0.03	5.6	3.1%	0.1%	-0.3%	0.3%
	4	3,583	0.79%	0.73	-0.02	4.6	3.1%	1.8%	3.3%	3.7%
	Winner	1,911	0.27%	0.74	-0.15	10.9	4.3%	7.5%	15.1%	14.9%
<b>Panel C</b>	<b>Quintile</b>	<b>me_company</b>	<b>ret_exc_lead1m</b>	<b>be_me</b>	<b>ni_me</b>	<b>ami_126d</b>	<b>rvol_252d</b>	<b>5 Day</b>	<b>10 Day</b>	<b>20 Day</b>
20 Day	Loser	1,049	0.63%	1.06	-0.37	13.3	4.9%	-4.7%	-9.1%	-17.8%
	2	2,818	0.62%	0.82	-0.06	5.9	3.4%	-1.1%	-2.5%	-5.3%
	3	3,613	0.84%	0.77	-0.02	5.3	3.0%	0.2%	0.0%	-0.1%
	4	3,677	0.82%	0.73	-0.02	4.9	3.1%	1.5%	2.5%	5.2%
	Winner	2,021	0.41%	0.71	-0.14	10.5	4.3%	5.4%	10.4%	22.2%

Table 5 presents the average characteristics of the Winner quintile and Loser quintile portfolio. Portfolios are formed using the excess return of the securities over period of 5 to 20 days, thus investigating short-term reversion and the possibility of making a profit with a contrarian strategy by applying single sorting. We will focus on the results of the Winner quintile and Loser quintile portfolios and their respective characteristics. For the 5 day calculation period, we observe an average `me_company` characteristic of 1,28 million for the Loser quintile portfolio and 1,82 million for the Winner quintile portfolio. The average size doesn't seem to differ significantly between loser and winner portfolios in terms of Market Equity. The Book Equity to Market Equity (`be_me`) is 0.98 is decreasing monotonically moving from Loser quintile to Winner quintile, which is logical given the fact that Losers have lost Market Equity and winners have gained Market Equity, given equal book values. We observe this inverse relationship for all three lookback periods. This indicates that the contrarian strategy naturally selects Loser companies that are relatively undervalued in comparison to the companies in the Winner portfolio. To account for this phenomena, we will use this characteristic in our double sorting procedure to address the positive value tilt in the contrarian strategy. The Loser portfolios have the most negative Net Income of all quintiles for all lookback periods. The second largest negative Net Income to Market Equity (`ni_me`) can be observed in the Winner portfolio. Regardless of the quintile and lookback period, the contrarian strategy selects stocks with a negative Net Income to Market Equity on average. This is likely to be driven by the large number of Micro and Nano stocks that have negative Net Income to Market Equity, as observed in the Table 2. The results show that both Loser and Winner portfolios consist of a high Amihud measure (`ami_126d`) of 13.2 for Loser portfolio and 11.4 for the Winner portfolio, indicating a clear bias towards illiquid stocks compared to quintiles 2, 3 and 4 that have equal illiquidity ratios. This means that both the Winner and Loser portfolios have low liquidity, likely driven by the presence of many Micro and Nano cap-sized firms. The other periods, 10-day lookback period and 20-day lookback period, show high illiquidity measure of 13.3 versus 10.9 and 13.3 versus 10.04, respectively. This motivates us to apply this characteristic in the double sorting process, where the contrarian portfolios will be formed by averaging over these characteristics. The average Realized Volatility over 252-days period (`rvol_252d`) for the Loser portfolio has a value of 4.9% versus the Winner portfolio's 4.4%, whereas quintile 2, 3 and 4 have much lower average Realized Volatilities. This indicates that the Loser and Winner quintile portfolios

select stocks with higher realized volatility on average. This may be driven by the recent overreaction, but is more likely that these stocks have higher volatilities and end up in the Winner and Loser portfolios due to their inherent volatility.

### 5.3 Loser-Winner Returns adjusted for Size, Valuation, Risk and Liquidity

In the previous section we reported substantial tilts towards firm characteristics obtained by single portfolio sorts for overreaction. Given those results, it is likely that the returns obtained from the contrarian strategy are strongly influenced by a multitude of firm characteristics. In this section, we attempt to adjust for these characteristics by applying double sorting procedure for portfolio formation of the contrarian strategy. We anticipate stronger results for the Loser compared to Winner portfolios.

**Table 6: Portfolio Returns of Loser and Winner portfolios by Size grouping**

In this table we report the Loser-Winner Portfolio Excess Returns of Equal Weighted Portfolios Per Size Grouping. Average Excess Returns are on a monthly frequency. Portfolios are formed by first splitting our sample into five size groupings, then per size grouping we sort securities on their total excess return over the past 5, 10 or 20 trading days. Five quintile portfolios are created every period per size grouping, resulting into 25 portfolios in total, the Loser portfolio consists of those securities with the lowest 20% excess returns, the Winner portfolio consists of securities with the highest 20% returns over the relevant lookback period. Portfolios are formed on monthly basis, there are 515 months in our sample, which runs from January 1980 to December 2022. The normal distribution is assumed in computing the P-values.

Panel A		Mega	Large	Small	Micro	Nano	Average
5 Day	Mean	0.45%	0.63%	0.62%	0.44%	1.41%	0.71%
	Std	3.69%	3.64%	3.53%	3.46%	5.43%	3.00%
	Sharpe	0.12	0.17	0.18	0.13	0.26	0.24
	Months	515	515	515	515	515	515
	T-Statistic	2.76	3.95	3.99	2.89	5.90	5.37
	P-value	0.3%	0.0%	0.0%	0.2%	0.0%	0.0%
Panel B		Mega	Large	Small	Micro	Nano	Average
10 Day	Mean	0.33%	0.41%	0.37%	0.24%	1.83%	0.64%
	Std	4.06%	4.10%	4.25%	4.37%	6.74%	3.90%
	Sharpe	0.08	0.10	0.09	0.06	0.27	0.16
	Months	515	515	515	515	515	515
	T-Statistic	1.83	2.30	2.00	1.27	6.16	3.71
	P-value	3.4%	1.1%	2.3%	10.2%	0.0%	0.0%
Panel C		Mega	Large	Small	Micro	Nano	Average
20 Day	Mean	0.13%	0.12%	0.04%	-0.08%	1.67%	0.38%
	Std	4.62%	4.81%	4.80%	4.93%	7.43%	4.44%
	Sharpe	0.03	0.03	0.01	-0.02	0.22	0.09
	Months	515	515	515	515	515	515
	T-Statistic	0.65	0.59	0.20	-0.35	5.09	1.93
	P-value	25.9%	27.9%	41.9%	63.7%	0.0%	2.7%

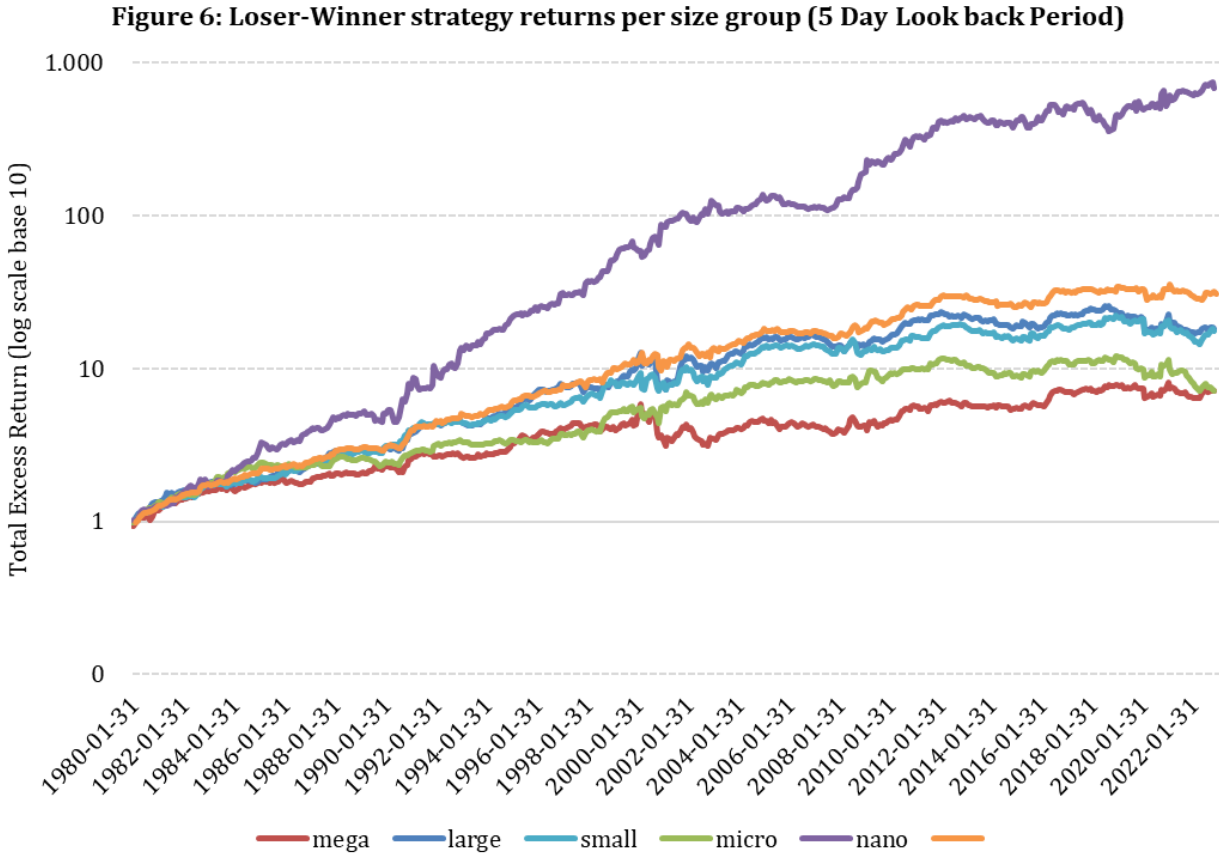
Table 6 reports the Mean, Std Deviation, Sharpe ratio and the T-Statistic of Loser - Winner Excess Portfolio Returns per Size grouping. For each Size group, we run the single sorting

procedure to select firms with overreaction and construct contrarian Loser – Winner portfolios positioned to profit from a reversion. The statistics are computed on a monthly frequency; for annualization, the average returns can be multiplied by 12, and Std Deviation and Sharpe ratio by 3.46, which is the square root of 12. We report the statistics per lookback period in three panels. The number of firms per group can be expected to be 40% of the number reported in Table 2. In Panel C, the standard lookback period of 20 trading days is reported; the average excess returns are low compared to those in Panel A and B. In fact, the T-Statistic in Panel C suggests that the returns gained from the contrarian strategy are no different from zero for all size groups but Nano stocks. If we average the excess returns per period across size groups, we can still earn a significant 0.38% on average per month. However, that is clearly driven by the large return earned by the contrarian strategy applied within set of Nano stocks. In that case, you're better off applying the contrarian investment strategy within Nano stocks as your Sharpe ratio will be much higher.

Looking at Panel B, we observe a clear improvement in Sharpe ratios, stemming from increased average excess returns and lower standard deviation. The reported T-Statistics are also much higher, and the contrarian strategy is providing significant positive returns on average, except for the Micro size group, which was the worst performer in Panel C with a 20-Day lookback. The improvement for Nano stocks is not that large compared to a 20-Day lookback period, but there is still an increase in average returns and lower standard deviation. It is likely for nano and micro stocks to have a larger survivorship bias. The listing and delisting turnover of micro and nano cap stocks is larger compared to larger-cap stocks.

If we narrow down to a 5-Day lookback period in Panel A, average excess returns increase across the board and are all significant at the 5% level. We see lower standard deviations and higher average returns, both contributing to higher Sharpe ratios. By lowering the lookback period from 20 Days to 5 Days, we can reduce the risk of the average Loser-Winner strategy by 33%. Thus, there appear to be clear advantages in reducing the lookback period and adjusting by size groups. Transaction costs will be significantly lower if the contrarian strategy is averaged over separate size groups, with the costs being the highest in the Micro and Nano groups, as those are the size groups with the highest Amihud illiquidity ratios.

The returns for each Loser-Winner strategy with a 5-Day lookback period are plotted in Figure 6 <sup>2</sup>below. We can observe the returns of the contrarian strategy applied within the Nano group to be very strong compared to the other size groups. We find the 5-Day lookback period to be optimal again in terms of Sharpe ratio, exhibiting a roughly two-times higher value compared to the 20-Days lookback period and a 50% higher value compared to the 10-Day lookback period.



<sup>2</sup> The returns are plotted on a log scale with base 10 to normalize the visualization.

**Table 7: Portfolio Returns of Loser and Winner portfolios by Characteristic grouping**

In this table we report the average Portfolio Excess Returns of Equal Weighted Portfolios over time per Characteristic Quintile. Average Excess Returns are on a monthly frequency. Portfolios are formed by first splitting our sample into five characteristic groupings then per characteristic quintile we sort securities on their total excess return over the past 5 trading days. Five quintile portfolios are created every period per characteristic grouping, resulting into 25 portfolios in total, the Loser portfolio consists of those securities with the lowest 20% excess returns, the Winner portfolio consists of securities with the highest 20% returns over the relevant lookback period. Portfolios are formed on monthly basis, there are 515 months in our sample, which runs from January 1980 to December 2022. The normal distribution is assumed in computing the P-values.

Characteristic	Quintile	Loser	2	3	4	Winner	Loser-Winner
Net Income / Market Equity	Low	0.90%	0.25%	0.37%	0.35%	-0.48%	1.38%
	2	0.70%	0.37%	0.29%	0.44%	-0.17%	0.87%
	3	1.06%	0.77%	0.65%	0.59%	0.27%	0.79%
	4	1.16%	0.98%	0.81%	0.72%	0.45%	0.71%
	High	1.48%	1.24%	1.15%	1.19%	0.71%	0.77%
	Mean	1.06%	0.72%	0.66%	0.66%	0.16%	0.90%
Characteristic	Quintile	Loser	2	3	4	Winner	Loser-Winner
Book Equity / Market Equity	Low	0.39%	0.26%	0.22%	0.30%	-0.15%	0.55%
	2	0.77%	0.54%	0.46%	0.42%	-0.02%	0.79%
	3	1.06%	0.73%	0.73%	0.58%	0.16%	0.90%
	4	1.24%	0.94%	0.80%	0.78%	0.37%	0.87%
	High	1.83%	1.27%	1.18%	1.29%	0.53%	1.30%
	Mean	1.06%	0.75%	0.68%	0.67%	0.18%	0.88%
Characteristic	Quintile	Loser	2	3	4	Winner	Loser-Winner
Amihud Illiquidity Ratio	Low	0.91%	0.92%	0.76%	0.59%	0.32%	0.60%
	2	1.00%	0.79%	0.63%	0.55%	0.19%	0.81%
	3	0.81%	0.72%	0.49%	0.52%	0.10%	0.71%
	4	0.72%	0.52%	0.48%	0.52%	-0.10%	0.82%
	High	1.45%	0.90%	0.87%	0.87%	-0.04%	1.49%
	Mean	0.98%	0.77%	0.65%	0.61%	0.09%	0.89%
Characteristic	Quintile	Loser	2	3	4	Winner	Loser-Winner
Realized Volatility	Low	1.09%	0.98%	0.84%	0.82%	0.68%	0.42%
	2	1.16%	1.00%	0.90%	0.81%	0.54%	0.62%
	3	1.10%	0.96%	0.78%	0.72%	0.41%	0.69%
	4	0.82%	0.70%	0.58%	0.55%	-0.08%	0.91%
	High	0.84%	0.30%	0.17%	0.07%	-1.11%	1.95%
	Mean	1.00%	0.79%	0.66%	0.59%	0.09%	0.92%

Table 7 reports the average excess return of the double sorting portfolios, with the second sort is done on a 5-Day lookback window. When we first sort by the Net Income to Market Equity and sort again by our overreaction proxy, we observe that the average return of the Loser portfolio rises linearly with the Net Income to Market Equity quintile. Thus, higher Net Income to Market results in a stronger reversion return for the Loser portfolio. The same effect can be observed for the Winner portfolio. This return pattern is likely to be driven by the Net Income to Market characteristic, as the same pattern can also be seen for the other quintile portfolios. Returns rise on average with the Net Income

characteristic. If we narrow in on the low Net Income to Market Equity quintile, we can see the effect often described in the literature, as in De Bond and Thaler (1985), where we observe positive average returns for the Loser portfolio and negative average returns for the Winner portfolio, this is a clear case of reversion. By averaging across the Net Income to Equity characteristic, we see a monotonic pattern of average returns appear, with higher returns for the Loser and lower returns for the Winner portfolios on average. The same pattern of average returns can be observed for the Book to Market Equity characteristic, albeit less pronounced in the size of returns. The reversion for the Winner portfolio can be clearly observed in the low and 2<sup>nd</sup> quintile of Book to Market Equity (-0.15% and -0.02%). Again, a monotonic pattern for average returns appears, thus indicating that averaging over characteristics reveals the reversion pattern more clearly.

The average returns across the Amihud illiquidity ratio appear to be more convex in nature, with higher returns in the lower and higher quintiles rather than in the middle. The returns averaged over the characteristic also reveal a monotonic reversion pattern. We can observe true reversion for the Winner portfolios in the highest Amihud portfolio sorts, where they lose on average -0.10% and -0.04% per month. These observations validate the notion of the adjusting for this stock characteristic, as it is instrumental in revealing the stock return reversion that is expected for overreaction.

The realized volatility quintiles show a monotonic pattern in average returns, where the average returns decrease with higher Realized Volatility. This phenomenon is often described in the literature as the Low Volatility Anomaly. By sorting for Losers and Winners within each Realized Volatility quintile, we reveal that the reversion is strongest in the High Volatility quintiles. The Winners lose -0.08% and -1.11% on average per month. Finally, the monotonic pattern of reversion averaged over Realized Volatility characteristic is again revealed.

These results summarize that adjusting the contrarian strategy of going long the Losers and going short the Winners makes more sense rather than the single portfolio sorts.

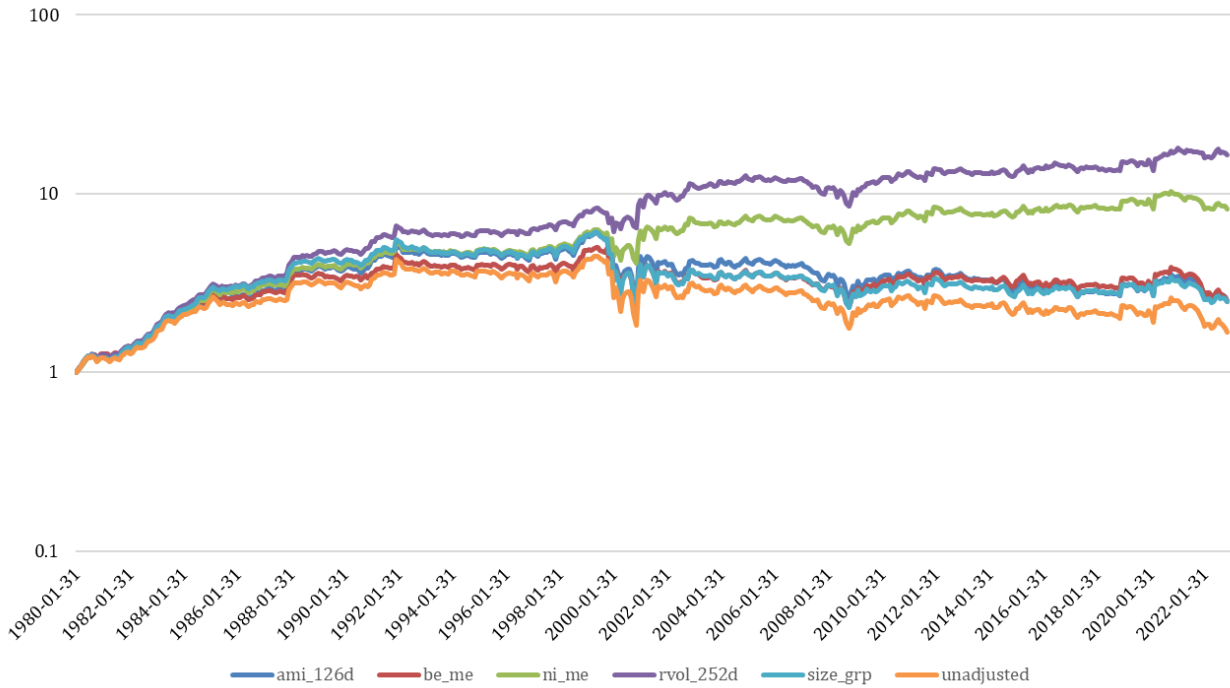
**Table 8: Portfolio Returns of Loser and Winner portfolios averaged over characteristics**

In this table we report the Loser-Winner Portfolio Excess Returns of Equal Weighted Portfolios Averaged over Characteristics. Average Excess Returns are on a monthly frequency. Portfolios are formed by first splitting our sample into five size characteristic, then per characteristic grouping we sort securities on their total excess return over the past 5, 10 or 20 trading days. Following this we average the Loser-Winner portfolio return over all five characteristic groupings. Five quintile portfolios are created every period per characteristic grouping, resulting into 25 portfolios in total, the Loser portfolio consists of those securities with the lowest 20% excess returns, the Winner portfolio consists of securities with the highest 20% returns over the relevant lookback period. Portfolios are formed on monthly basis, there are 515 months in our sample, which runs from January 1980 to December 2022. The normal distribution is assumed in computing the P-values.

Panel A		<b>ami_126d</b>	<b>be_me</b>	<b>ni_me</b>	<b>rvol_252d</b>	<b>size_grp</b>	<b>unadjusted</b>
5 Day	Mean	0.65%	0.56%	0.73%	0.82%	0.64%	0.54%
	Std	3.18%	3.07%	2.64%	2.60%	3.03%	3.46%
	Sharpe	0.20	0.18	0.28	0.31	0.21	0.16
	Months	515	515	515	515	515	515
	T-Statistic	4.63	4.18	6.25	7.12	4.78	3.57
	P-value	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Panel B		<b>ami_126d</b>	<b>be_me</b>	<b>ni_me</b>	<b>rvol_252d</b>	<b>size_grp</b>	<b>unadjusted</b>
10 Day	Mean	0.52%	0.54%	0.73%	0.84%	0.54%	0.49%
	Std	4.21%	4.08%	3.40%	3.15%	3.99%	4.55%
	Sharpe	0.12	0.13	0.22	0.27	0.13	0.11
	Months	515	515	515	515	515	515
	T-Statistic	2.80	2.99	4.90	6.04	3.06	2.42
	P-value	0.3%	0.1%	0.0%	0.0%	0.1%	0.8%
Panel C		<b>ami_126d</b>	<b>be_me</b>	<b>ni_me</b>	<b>rvol_252d</b>	<b>size_grp</b>	<b>unadjusted</b>
20 Day	Mean	0.29%	0.27%	0.48%	0.61%	0.28%	0.22%
	Std	4.75%	4.54%	3.82%	3.50%	4.54%	5.09%
	Sharpe	0.06	0.06	0.13	0.17	0.06	0.04
	Months	515	515	515	515	515	515
	T-Statistic	1.37	1.37	2.85	3.92	1.39	1.00
	P-value	8.6%	8.5%	0.2%	0.0%	8.3%	16.0%

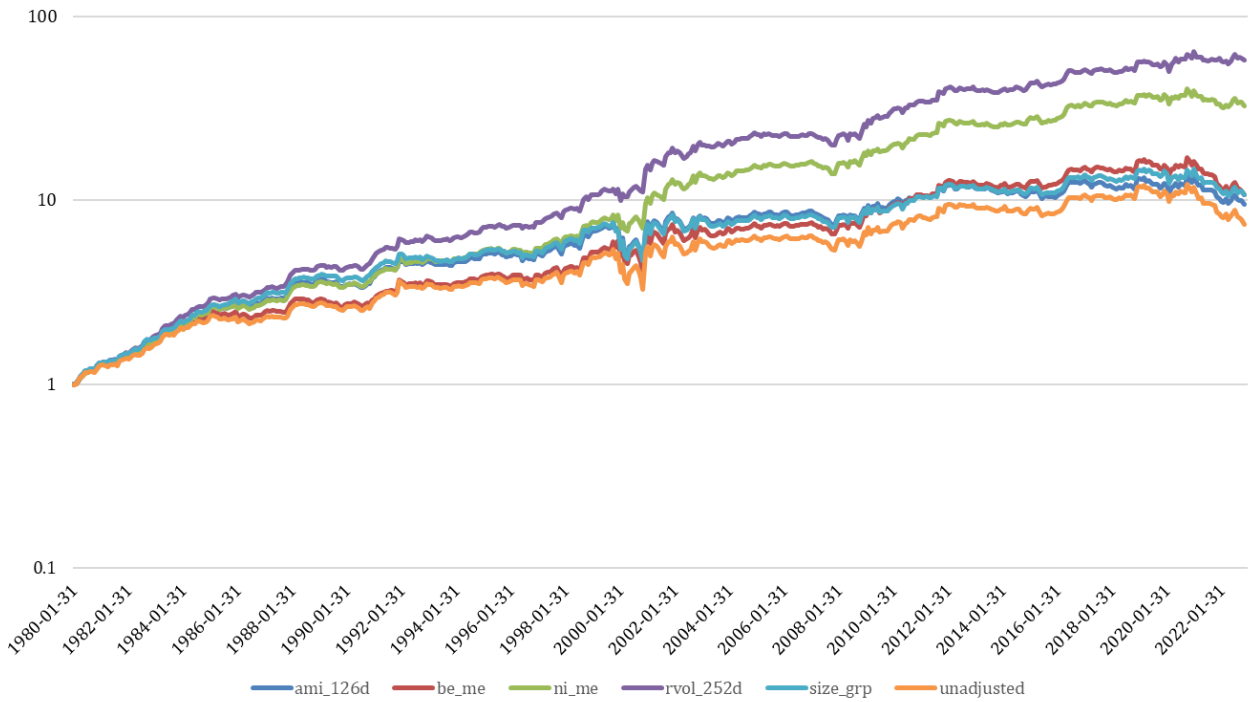
Table 8 reports the Mean, Std Deviation, Sharpe ratio and the T-Statistic of Loser - Winner Excess Portfolio Returns per characteristic adjustment. For each characteristic, we run the double sorting procedure to select firms with overreaction and construct contrarian Loser - Winner portfolios that are positioned to profit from a reversion.

**Figure 9: Loser-Winner strategy returns averaged over characteristics (20 Day Look back Period)**



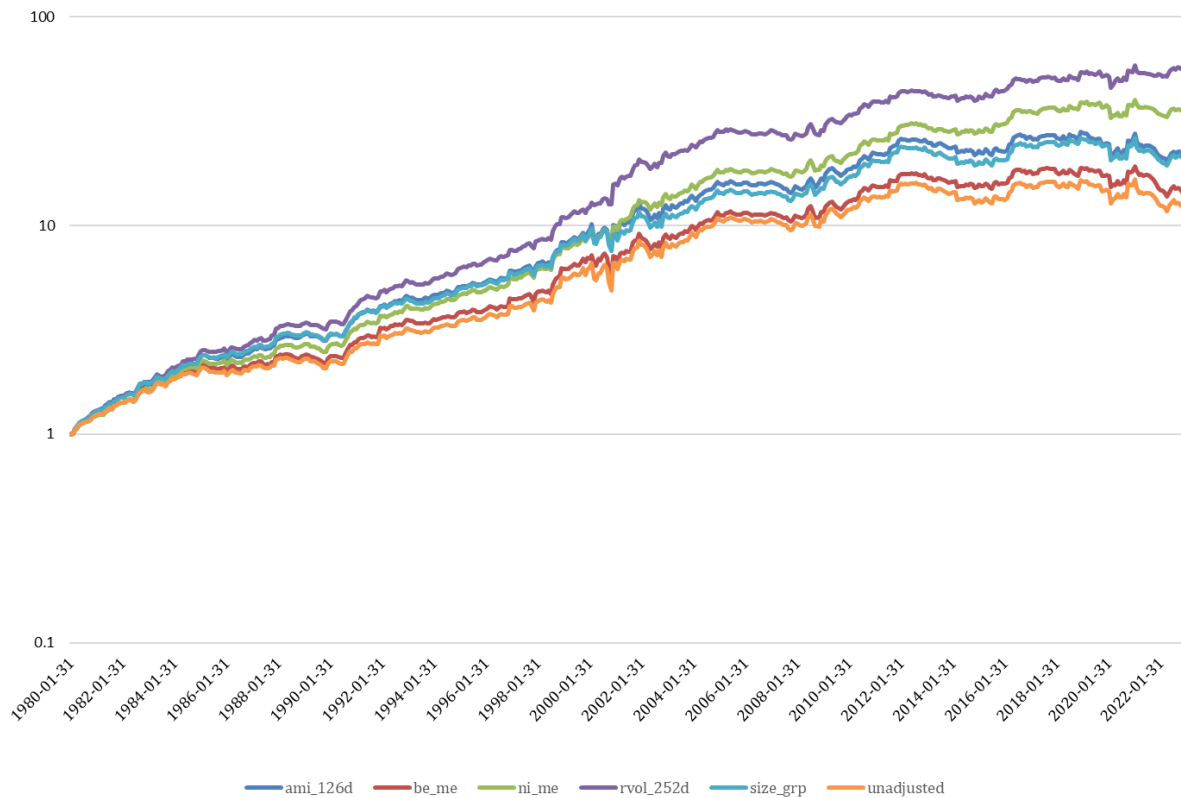
Starting off in Panel C, the standard lookback period of 20 Trading days is reported; the average excess returns are low in comparison to those in Panel A and B. In fact, the T-Statistic in Panel C suggests that the returns gained from the contrarian strategy are no different from zero for all characteristics but Net Income to Market Equity and Realized Volatility. The average excess returns are also much higher for these adjusted contrarian strategies, where the returns for the Amihud illiquidity ratio, Book Equity to Market Equity ratio and size grouping are in line with that of the unadjusted strategy. Thus, for a standard lookback of 20 Days, you're better off applying the contrarian investment strategy by adjusting for Realized Volatility and/or Net Income to Market Equity. The final strategy's Sharpe ratio will be much higher.

Figure 8 : Loser-Winner strategy returns averaged over characteristics (10 Day Look back Period)



For Panel B, a noticeable enhancement in Sharpe ratios is evident, attributed to increased average excess returns and reduced standard deviation. Similar improvements are observed for the Size Grouping adjustment. The reported T-Statistic also exhibit a substantial increase, affirming that the contrarian strategy consistently delivers significant positive returns on average. Once again, the adjustment based on Net Income to Market Equity and Realized Volatility prove to be the most effective, leading to higher average returns and lower standard deviation.

Figure 7: Loser-Winner strategy returns averaged over characteristics (5 Day Look back Period)



Examining the 5-Day lookback period in Panel A, there is a universal increase in average excess returns, all statistically significant at the 1% level. The lower standard deviations and higher average returns collectively contribute to elevated Sharpe ratios. Decreasing the lookback period from 20 Days to 5 Days results in a risk reduction of 31% for the Net Income to Market Equity adjusted Loser-Winner strategy. Thus, there seem to be distinct advantages in reducing the lookback period and incorporating characteristic adjustments. For this strategy to be profitable, its excess returns need to be positive after accounting for transaction costs. This way, we can exclude the lack of liquidity as the primary driver of reversal profits.

## 6 Strategy Factor Model Analysis

In this section, we conduct a time series regression analysis to estimate the Fama-French Five Factor Model, incorporating the Momentum factor. The objective is to determine whether the contrarian strategy has the potential to generate excess returns beyond the risk factors embedded in the model. This entails testing the hypothesis whether the alpha is equal to zero. A significant T-Statistics would imply that the observed results are uncommon that the hypothesis of zero alpha may not hold true. If this is the case, it indicates that the contrarian strategy can achieve excess returns by leveraging reversion resulting from previous overreactions.

### 6.1 Loadings of the Loser – Winner Portfolio Returns

We present the estimates of Factor Loadings for the Loser-Winner Portfolio Returns in Table 9. The estimates are reported for five distinct double sorted Loser-Winner portfolios and the unadjusted Loser-Winner Portfolios based on the 5-Day lookback period. The results for the 10-Day and 20-Day lookback period are included in the appendix as they do not offer additional insights into the strategy returns.

**Table 9: Factor Model Estimates of Loser and Winner Portfolio Returns**

In this table we report the Factor Model Estimates of Loser-Winner Portfolio Excess Returns of Equal Weighted Portfolios Averaged over Characteristics. The Factor that is estimated is the The Fama and French Five Factor Model with the Momentum factor as a sixth factor. Standard Errors are Newey-West Heteroskedasticity Autocorrelation Corrected Standard Errors using 6 lags. Average Excess Returns are on a monthly frequency. Portfolios are formed by first splitting our sample into five size characteristic, then per characteristic grouping we sort securities on their total excess return over the past 5 trading days. Following this we average the Loser-Winner portfolio return over all five characteristic groupings. Five quintile portfolios are created every period per characteristic grouping, resulting into 25 portfolios in total, the Loser portfolio consists of those securities with the lowest 20% excess returns, the Winner portfolio consists of securities with the highest 20% returns over the relevant lookback period. Portfolios are formed on monthly basis, there are 515 months in our sample, which runs from January 1980 to December 2022. The normal distribution is assumed in computing the P-values.

	<b>ami_126d</b>	<b>be_me</b>	<b>ni_me</b>	<b>rvol_252d</b>	<b>size_grp</b>	<b>unadjusted</b>
<b>alpha</b>	0.0086*** (0.0017)	0.0077*** (0.0016)	0.0088*** (0.0014)	0.0096*** (0.0015)	0.0081*** (0.0015)	0.0079*** (0.0019)
<b>MKT-RF</b>	0.0544 (0.0368)	0.0435 (0.0355)	0.0477 (0.0294)	0.0428 (0.0315)	0.0717** (0.0332)	0.0266 (0.0426)
<b>SMB</b>	0.1495*** (0.0526)	0.1212** (0.0562)	0.1086** (0.0470)	0.1078** (0.0480)	0.1327*** (0.0512)	0.1372** (0.0605)
<b>HML</b>	0.0155 (0.0945)	-0.0286 (0.0922)	0.0093 (0.0750)	0.0229 (0.0700)	0.0325 (0.0895)	-0.0082 (0.0986)
<b>RMW</b>	-0.1646* (0.0856)	-0.1387 (0.0859)	-0.0941 (0.0654)	-0.0638 (0.0530)	-0.1521* (0.0868)	-0.1839* (0.0943)
<b>CMA</b>	-0.3840*** (0.1305)	-0.3443*** (0.1289)	-0.2737*** (0.0995)	-0.2464*** (0.0893)	-0.3674*** (0.1231)	-0.3854*** (0.1415)
<b>MOM</b>	-0.1653** (0.0772)	-0.1565** (0.0695)	-0.1335*** (0.0489)	-0.1716*** (0.0545)	-0.1289** (0.0548)	-0.1751** (0.0883)
<b>N</b>	515	515	515	515	515	516
<b>R-squared</b>	21.3%	19.3%	17.0%	18.4%	19.9%	18.5%

\* p<.1, \*\* p<.05, \*\*\*p<.01

The factor exposures of the Loser-Winner Portfolio Returns remain highly consistent across the six adjusted contrarian strategies. The factor loading on the Market Factor (**MKT-RF**) is positive on average but too noisy to provide any explanatory power, except for the **size\_grp** adjusted strategy, which is significant at the 5% level. This significance is difficult to pinpoint but may stem from the averaging effect over the five size groupings. Consequently, the contrarian strategy can be considered market neutral. The factor loading on the Size Factor (**SMB**) is consistently positive and significant for all strategies, the reason is clear, due to the equal weighting of securities for the Loser and Winner portfolios.

As we are equal weighting, it is reasonable to assume that we are overweighting small capitalized stocks and underweighting large capitalized stocks. If portfolios were value-weighted, the resulting loading would likely be neutral or negative. The loadings on the Value factor (**HML**) are not different from zero for all six strategies, indicating that the contrarian strategy does not result in portfolios that are sensitive to valuation. The loadings on the Profitability factor (**RMW**) are negative across all portfolios, with the most negative loading for the unadjusted strategy. The contrarian strategy is prone to selecting stocks with weak profitability, however, adjusting for Book Equity to Market Equity ratio, E/P ratio or Realized Volatility (most effective) mitigates this negative loading. The average return on the Profitability factor is positive, suggesting a return drag for the unadjusted strategy. Adjustments can help avoid this drag. The factor loadings of the Investment factor (**CMA**) have the largest size, are consistently negative across all strategies and are highly significant. The Realized Volatility adjusted strategy is the most effective in reducing the factor loading by almost a third compared to the unadjusted strategy, but remains strongly negative. This indicates that the contrarian strategies select stocks that have high (aggressive) reinvestment ratios, which indicates a negative return drag for the contrarian strategy. The factor loading on the Momentum (**MOM**) is negative across the board, which is in line with the contrarian strategy that goes Long the losers and short the Winners, explaining the sign and size of the factor loading.

## 6.2 Alphas of Loser-Winner Portfolio Returns

We present the Alphas of the Loser-Winner Portfolio Excess Returns in Table 10. The estimates cover five different double sorted Loser-Winner portfolios and the unadjusted Loser-Winner Portfolio for the 5-Day, 10-Day and 20-Day lookback period.

**Table 10: Factor Model Alphas and Standard Errors of Loser and Winner Portfolio Returns**

In this table we report the Alphas and Standard Errors of Loser-Winner Portfolio Excess Returns of Equal Weighted Portfolios Averaged over Characteristics. The Alphas are estimated using The Fama and French Five Factor Model with the Momentum factor as a sixth factor. Standard Errors are Newey-West Heteroskedasticity Autocorrelation Corrected Standard Errors using 6 lags. Average Excess Returns are on a monthly frequency. Portfolios are formed by first splitting our sample into five size characteristic, then per characteristic grouping we sort securities on their total excess return over the past 5, 10 or 20 trading days. Following this we average the Loser-Winner portfolio return over all five characteristic groupings. Five quintile portfolios are created every period per characteristic grouping, resulting into 25 portfolios in total, the Loser portfolio consists of those securities with the lowest 20% excess returns, the Winner portfolio consists of securities with the highest 20% returns over the relevant lookback period. Portfolios are formed on monthly basis, there are 515 months in our sample, which runs from January 1980 to December 2022. The normal distribution is assumed in computing the P-values.

Lookback period	Statistic	<b>ami_126d</b>	<b>be_me</b>	<b>ni_me</b>	<b>rvol_252d</b>	<b>size_grp</b>	<b>unadjusted</b>
5 Day	alpha	0.0086***	0.0077***	0.0088***	0.0096***	0.0081***	0.0079***
	Std Err	(0.0017)	(0.0016)	(0.0014)	(0.0015)	(0.0015)	(0.0019)
10 Day	alpha	0.0075***	0.0078***	0.0087***	0.0097***	0.0070***	0.0073***
	Std Err	(0.0026)	(0.0024)	(0.0020)	(0.0018)	(0.0024)	(0.0027)
20 Day	alpha	0.0046*	0.0045*	0.0058***	0.0071***	0.0029	0.0043
	Std Err	(0.0027)	(0.0024)	(0.0020)	(0.0019)	(0.0026)	(0.0028)

\* p<.1, \*\* p<.05, \*\*\*p<.01

The Alpha obtained from an unadjusted contrarian strategy, which selects Losers and Winners with a 5 - Trading Days lookback period, averages 0.79% per month. The highest alpha, reaching 0.96%, is achieved when the double sorting procedure is applied in conjunction with the realized volatility (**rvol\_252d**) characteristic of stocks. There is a clear inverse relation between reducing the lookback period and an increase in the alpha, with the strongest change observed from 20 Days to 10 Days. At a 10-Day lookback period, alphas are highly significant at the 1% level for all contrarian strategies. The double sorting procedure applied with the realized volatility proves to be the most effective in enhancing the alpha for all lookback periods. The Standard deviation of the alpha is reduced substantially when adjusting for any characteristic, with the most effective approach being the adjustment for E/P ratio (**ni\_me**). Adjusting for Size or Realized Volatility yields comparable results, and this consistency holds for all three lookback periods. Given these results, we can be confident that the contrarian strategies generate strong positive excess returns after accounting for Risk, Liquidity and other characteristics. We find the 5-Day lookback period to be optimal, exhibiting the highest

alphas for four characteristics (ami\_126d; ni\_me; size\_grp; unadjusted) compared to the 10 or 20-Day alphas. Most importantly, the stand error is the lowest for the 5-Day lookback period compared to the 10 and 20-Day period.

## 7. Conclusion

**Table 10.1: Summary Results**

In this table we report a summary of the results for the Loser-Winner Portfolio. We report the Excess Return (Loser-Winner), the Sharpe ratio and the Alphas for the contrarian strategies (Double Sort & Single Sort method).

Lookback Period	Varibale	Double-Sort					Single-Sort
		ami_126d	be_me	ni_me	rvol_252d	size_grp	unadjusted
<b>5-Day</b>	Excess Return (Loser-Winner)	0.65%	0.56%	0.79%	0.82%	0.64%	0.54%
	Sharpe ratio	0.20	0.18	0.28	0.31	0.21	0.16
	Alphas	0.0086***	0.0077***	0.0088***	0.0096***	0.0081***	0.0079***
<b>10-Day</b>	Excess Return (Loser-Winner)	0.52%	0.54%	0.73%	0.84%	0.54%	0.49%
	Sharpe ratio	0.12	0.13	0.22	0.27	0.13	0.11
	Alphas	0.0075***	0.0078***	0.0087***	0.0097***	0.0070***	0.0073***
<b>20-Day</b>	Excess Return (Loser-Winner)	0.29%	0.27%	0.48%	0.61%	0.28%	0.22%
	Sharpe ratio	0.06	0.06	0.13	0.17	0.06	0.04
	Alphas	0.0046*	0.0045*	0.0058***	0.0071***	0.0029	0.0043

\* p<.1, \*\* p<.05, \*\*\*p<.01

This thesis commenced by investigating the evidence of the Overreaction Hypothesis on the stocks of the entire US market during the period 1980-2022, utilizing single and double sorting methods to create contrarian investment portfolios. While the results from the single sorting procedure were weak for the 20-Day lookback period, a reduction in the lookback period to 10 or 5 Trading Days revealed that reversion is still robust in the US market across all size segments.

Through the single sorting procedure on Total Excess returns, we demonstrated that the quintile portfolios of Loser and Winner stocks exhibit biases toward characteristics such as Market Equity, Net Income to Market Equity, Book Equity To Market Equity, Realized

Volatility and the Amihud Illiquidity. To address these tilts, we opted for the double sorting procedure that has become standard since the introduction of the Fama-French Three Factor Model. The double sorting procedure revealed monotonic average returns for the contrarian investment strategy, once again confirming that reversion is strongly present in the US market.

*If we employ a contrarian strategy ourselves, can the excess return of alpha be generated and can such outcomes be explained by the market factors?*

Based on the regression results, we found statistically significant and positive alphas for the contrarian strategy. However, we could not fully explain the excess returns using the Market Factors of the Fama-French Five-Factor model, including the Momentum Factor.

*Can a regular investor profit from the Overreaction Hypothesis if risk, liquidity and size also have been accounted for?*

The study suggests that the regular investor can profit from the Overreaction Hypothesis by accounting for risk, liquidity and size, assuming that the investor has a sizeable amount of capital to invest in this strategy. The analysis has demonstrated a significant positive alpha that can be harvested from the contrarian strategy on a month – by – month basis.

For future research, it is recommended to deduct transactions costs from the Loser – Winner portfolio returns, shedding light on whether the contrarian strategy remains profitable accounting for trading expanses. The anticipated high turnover and illiquidity ratios may result in elevated bid-ask spread, posing challenges to the viability of the strategy. However, the ultimate assessment of whether the costs are prohibitively high depends on additional factors, including infrastructure and data costs. In financial analysis and trading strategies, the evaluation of costs goes beyond the immediate transaction expenses. The infrastructure costs encompass the technological foundation necessary for the execution and maintenance of the strategy. Additionally, the access to high-quality and real time data is essential for making informed decisions and optimizing trading strategies.

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## 9. Appendix

### Capital Asset Pricing Model:

$$E[R_i] = R_f + \beta_i(E[R_m] - R_f)$$

where:

$E[R_i]$  is the expected return,  $R_f$  is risk-free rate,  $\beta_i$  is beta of the investment, finally  $(E[R_m] - R_f)$  measures the market risk premium.

### Fama-French 3 Factor model:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \beta_2SMB_t + \beta_3HML_t + \varepsilon_{it}$$

$R_{it}$  is total return of a stock or portfolio  $i$  at time  $t$ .  $R_{ft}$  =risk free rate of return at time  $t$ .  $R_{mt}$  total market portfolio return at time  $t$ .  $R_{it} - R_{ft}$  is expected excess return.  $R_{mt} - R_{ft}$  =excess return on the market portfolio (index).  $SMB_t$  =return of the size factor (small minus big).  $HML_t$  is the return of the value factor (high minus low)

### Carhart model:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \beta_2SMB_t + \beta_3HML_t + \beta_4MOM_t + \varepsilon_{it}$$

This is the Fama-French 3 Factor model with Momentum as an additional factor. Momentum (MOM) is the return difference between diversified portfolios of stocks with High and Low Momentum, which is measured as the total return over the prior 12 months, adjusted for the 1-Month Reversal effect.

### Fama-French 5 Factor model:

$$R_{it} = \alpha_i + \beta_iMKT + \beta_2SMB_t + \beta_3HML_t + \beta_4RMW + \beta_5CMA$$

where:

Market Return (MKT) is the excess market return. It is the return on the value-weighted market portfolio. Small Minus Big (SBM) is the return for a diversified portfolio of Small-cap stocks minus the return on a diversified portfolio of Big-cap stocks, this factor is associated with size-effect, smaller companies may outperform larger ones over a certain period of time. High Minus Low (HML) is return difference between diversified portfolios

of stocks with High and Low Book-to-Market ratios. Robust Minus Weak (RMW) is the difference between the returns on diversified portfolios of stocks with Robust (high and steady) and Weak (low) profitability. Conservative Minus Aggressive (CMA) is the difference between the returns on diversified portfolios of the stocks of low and high investment firms, which we call conservative and aggressive. Here, low/high investment means reinvestment ratio is low/high.

**Fama-French 5 Factor model inc. Momentum Factor:**

$$R_{it} = \alpha_i + \beta_1MKT + \beta_2SMB_t + \beta_3HML_t + \beta_4RMW + \beta_5CMA + \beta_6MOM$$

This is Fama-French 5 Factor Model with Momentum as an additional Factor. This model is applied in our study.

Table 11: Loser and Winner portfolios by Characteristic grouping (10 Day)

**Table 11: Portfolio Returns of Loser and Winner portfolios by Characteristic grouping**

In this table we report the average Portfolio Excess Returns of Equal Weighted Portfolios over time per Characteristic Quintile. Average Excess Returns are on a monthly frequency. Portfolios are formed by first splitting our sample into five characteristic groupings then per characteristic quintile we sort securities on their total excess return over the past 10 trading days. Five quintile portfolios are created every period per characteristic grouping, resulting into 25 portfolios in total, the Loser portfolio consists of those securities with the lowest 20% excess returns, the Winner portfolio consists of securities with the highest 20% returns over the relevant lookback period. Portfolios are formed on monthly basis, there are 515 months in our sample, which runs from January 1980 to December 2022. The normal distribution is assumed in computing the P-values.

Characteristic	Quintile	Loser	2	3	4	Winner	Loser-Winner
Net Income / Market Equity	Low	1.06%	0.07%	0.25%	0.30%	-0.39%	1.45%
	2	0.53%	0.33%	0.33%	0.43%	-0.04%	0.58%
	3	0.99%	0.79%	0.73%	0.60%	0.26%	0.73%
	4	1.20%	0.89%	0.86%	0.74%	0.44%	0.77%
	High	1.52%	1.25%	1.15%	1.18%	0.64%	0.88%
	Mean	1.06%	0.67%	0.66%	0.65%	0.18%	0.88%
Characteristic	Quintile	Loser	2	3	4	Winner	Loser-Winner
Book Equity / Market Equity	Low	0.13%	0.10%	0.23%	0.47%	-0.03%	0.16%
	2	0.70%	0.54%	0.47%	0.48%	-0.03%	0.74%
	3	1.09%	0.70%	0.70%	0.58%	0.14%	0.94%
	4	1.37%	0.90%	0.83%	0.70%	0.29%	1.07%
	High	1.96%	1.21%	1.21%	1.07%	0.62%	1.34%
	Mean	1.05%	0.69%	0.69%	0.66%	0.20%	0.85%
Characteristic	Quintile	Loser	2	3	4	Winner	Loser-Winner
Amihud Illiquidity Ratio	Low	0.77%	0.86%	0.83%	0.65%	0.39%	0.38%
	2	0.81%	0.78%	0.69%	0.63%	0.25%	0.56%
	3	0.79%	0.57%	0.58%	0.50%	0.20%	0.59%
	4	0.72%	0.43%	0.53%	0.47%	-0.02%	0.74%
	High	1.75%	0.93%	0.84%	0.70%	-0.19%	1.94%
	Mean	0.97%	0.72%	0.69%	0.59%	0.13%	0.84%
Characteristic	Quintile	Loser	2	3	4	Winner	Loser-Winner
Realized Volatility	Low	1.17%	0.94%	0.93%	0.77%	0.61%	0.56%
	2	1.19%	1.01%	0.94%	0.80%	0.48%	0.71%
	3	1.03%	0.94%	0.81%	0.70%	0.47%	0.55%
	4	0.73%	0.53%	0.59%	0.60%	0.09%	0.65%
	High	0.85%	0.29%	0.16%	0.03%	-1.05%	1.90%
	Mean	0.99%	0.74%	0.68%	0.58%	0.12%	0.88%

Table 12: Loser and Winner portfolios by Characteristic grouping (20 Day)

**Table 12: Portfolio Returns of Loser and Winner portfolios by Characteristic grouping**

In this table we report the average Portfolio Excess Returns of Equal Weighted Portfolios over time per Characteristic Quintile. Average Excess Returns are on a monthly frequency. Portfolios are formed by first splitting our sample into five characteristic groupings then per characteristic quintile we sort securities on their total excess return over the past 20 trading days. Five quintile portfolios are created every period per characteristic grouping, resulting into 25 portfolios in total, the Loser portfolio consists of those securities with the lowest 20% excess returns, the Winner portfolio consists of securities with the highest 20% returns over the relevant lookback period. Portfolios are formed on monthly basis, there are 515 months in our sample, which runs from January 1980 to December 2022. The normal distribution is assumed in computing the P-values.

Characteristic	Quintile	Loser	2	3	4	Winner	Loser-Winner
Net Income / Market Equity	Low	0.87%	0.15%	0.29%	0.39%	-0.41%	1.28%
	2	0.42%	0.15%	0.25%	0.42%	0.25%	0.18%
	3	0.84%	0.70%	0.72%	0.63%	0.43%	0.42%
	4	1.06%	0.96%	0.83%	0.75%	0.51%	0.54%
	High	1.40%	1.25%	1.22%	1.13%	0.75%	0.64%
	Mean	0.92%	0.64%	0.66%	0.66%	0.31%	0.61%
Characteristic	Quintile	Loser	2	3	4	Winner	Loser-Winner
Book Equity / Market Equity	Low	-0.02%	-0.14%	0.15%	0.42%	0.28%	-0.30%
	2	0.48%	0.55%	0.50%	0.41%	0.19%	0.28%
	3	0.91%	0.72%	0.68%	0.64%	0.24%	0.67%
	4	1.20%	0.90%	0.82%	0.81%	0.32%	0.87%
	High	1.92%	1.24%	1.22%	1.08%	0.51%	1.40%
	Mean	0.90%	0.65%	0.67%	0.67%	0.31%	0.58%
Characteristic	Quintile	Loser	2	3	4	Winner	Loser-Winner
Amihud Illiquidity Ratio	Low	0.58%	0.81%	0.82%	0.74%	0.55%	0.04%
	2	0.68%	0.62%	0.73%	0.66%	0.47%	0.21%
	3	0.59%	0.53%	0.56%	0.46%	0.49%	0.10%
	4	0.55%	0.49%	0.48%	0.55%	0.07%	0.47%
	High	1.72%	1.01%	0.86%	0.70%	-0.27%	1.98%
	Mean	0.82%	0.69%	0.69%	0.62%	0.26%	0.56%
Characteristic	Quintile	Loser	2	3	4	Winner	Loser-Winner
Realized Volatility	Low	1.08%	1.01%	0.92%	0.82%	0.60%	0.48%
	2	1.09%	1.04%	0.91%	0.76%	0.61%	0.48%
	3	0.83%	0.87%	0.86%	0.76%	0.62%	0.21%
	4	0.59%	0.43%	0.59%	0.59%	0.34%	0.25%
	High	0.63%	0.23%	0.20%	0.10%	-0.89%	1.53%
	Mean	0.85%	0.72%	0.70%	0.61%	0.26%	0.59%

Table 13: Factor Model Estimates (10 Day)

**Table 13: Factor Model Estimates of Loser and Winner Portfolio Returns**

In this table we report the Factor Model Estimates of Loser-Winner Portfolio Excess Returns of Equal Weighted Portfolios Averaged over Characteristics. The Factor that is estimated is the The Fama and French Five Factor Model with the Momentum factor as a sixth factor. Standard Errors are Newey-West Heteroskedasticity Autocorrelation Corrected Standard Errors using 6 lags. Average Excess Returns are on a monthly frequency. Portfolios are formed by first splitting our sample into five size characteristic, then per characteristic grouping we sort securities on their total excess return over the past 10 trading days. Following this we average the Loser-Winner portfolio return over all five characteristic groupings. Five quintile portfolios are created every period per characteristic grouping, resulting into 25 portfolios in total, the Loser portfolio consists of those securities with the lowest 20% excess returns, the Winner portfolio consists of securities with the highest 20% returns over the relevant lookback period. Portfolios are formed on monthly basis, there are 515 months in our sample, which runs from January 1980 to December 2022. The normal distribution is assumed in computing the P-values.

	<b>ami_126d</b>	<b>be_me</b>	<b>ni_me</b>	<b>rvol_252d</b>	<b>size_grp</b>	<b>unadjusted</b>
<b>alpha</b>	0.0075*** (0.0026)	0.0078*** (0.0024)	0.0087*** (0.0020)	0.0097*** (0.0018)	0.0070*** (0.0024)	0.0073*** (0.0027)
<b>MKT-RF</b>	0.0763 (0.0595)	0.0584 (0.0574)	0.0872* (0.0451)	0.0825* (0.0421)	0.1095** (0.0540)	0.0594 (0.0654)
<b>SMB</b>	0.1515 (0.0923)	0.1632* (0.0876)	0.1280* (0.0745)	0.1060 (0.0695)	0.1163 (0.0871)	0.1369 (0.1037)
<b>HML</b>	0.0692 (0.1032)	-0.0150 (0.1047)	0.0305 (0.0769)	0.0438 (0.0710)	0.1085 (0.0958)	0.0313 (0.1096)
<b>RMW</b>	-0.0089 (0.1386)	-0.0364 (0.1281)	0.0228 (0.1039)	0.0367 (0.0930)	0.0265 (0.1423)	-0.0478 (0.1491)
<b>CMA</b>	-0.5366*** (0.1670)	-0.4792*** (0.1669)	-0.3532*** (0.1235)	-0.3084*** (0.1069)	-0.5345*** (0.1607)	-0.4952*** (0.1709)
<b>MOM</b>	-0.2681* (0.1461)	-0.2488* (0.1343)	-0.2053** (0.1020)	-0.2327*** (0.0881)	-0.2236* (0.1301)	-0.2752* (0.1534)
<b>N</b>	515	515	515	515	515	516
<b>R-squared</b>	19.0%	18.5%	17.4%	20.1%	18.3%	16.2%

\* p<.1, \*\* p<.05, \*\*\*p<.01

Table 14: Factor Model Estimates (20 Day)

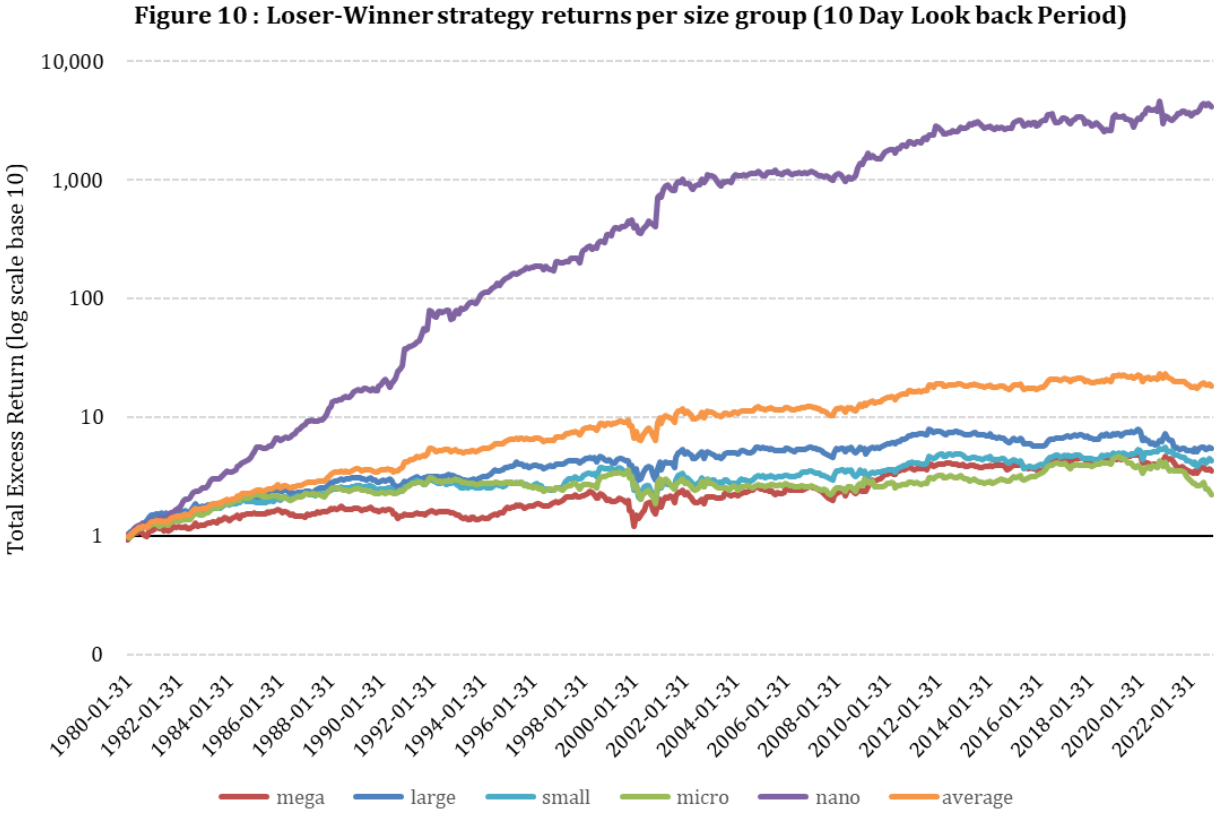
**Table 14: Factor Model Estimates of Loser and Winner Portfolio Returns**

In this table we report the Factor Model Estimates of Loser-Winner Portfolio Excess Returns of Equal Weighted Portfolios Averaged over Characteristics. The Factor that is estimated is the The Fama and French Five Factor Model with the Momentum factor as a sixth factor. Standard Errors are Newey-West Heteroskedasticity Autocorrelation Corrected Standard Errors using 6 lags. Average Excess Returns are on a monthly frequency. Portfolios are formed by first splitting our sample into five size characteristic, then per characteristic grouping we sort securities on their total excess return over the past 20 trading days. Following this we average the Loser-Winner portfolio return over all five characteristic groupings. Five quintile portfolios are created every period per characteristic grouping, resulting into 25 portfolios in total, the Loser portfolio consists of those securities with the lowest 20% excess returns, the Winner portfolio consists of securities with the highest 20% returns over the relevant lookback period. Portfolios are formed on monthly basis, there are 515 months in our sample, which runs from January 1980 to December 2022. The normal distribution is assumed in computing the P-values.

	<b>ami_126d</b>	<b>be_me</b>	<b>ni_me</b>	<b>rvol_252d</b>	<b>size_grp</b>	<b>unadjusted</b>
<b>alpha</b>	0.0046* (0.0027)	0.0045* (0.0024)	0.0058*** (0.0020)	0.0071*** (0.0019)	0.0029 (0.0026)	0.0043 (0.0028)
<b>MKT-RF</b>	0.1674*** (0.0650)	0.1516** (0.0605)	0.1524*** (0.0498)	0.1303*** (0.0456)	0.2006*** (0.0602)	0.1376* (0.0708)
<b>SMB</b>	0.1144 (0.1164)	0.1257 (0.1154)	0.1090 (0.0944)	0.0989 (0.0811)	0.0534 (0.1095)	0.1261 (0.1285)
<b>HML</b>	-0.0100 (0.0988)	-0.0814 (0.1036)	-0.0517 (0.0781)	-0.0106 (0.0714)	0.0451 (0.0946)	-0.0219 (0.1124)
<b>RMW</b>	-0.0162 (0.1951)	-0.0252 (0.1872)	0.0243 (0.1457)	0.0169 (0.1183)	0.0261 (0.2023)	-0.0545 (0.2078)
<b>CMA</b>	-0.3451** (0.1559)	-0.3285** (0.1619)	-0.2028* (0.1150)	-0.1512 (0.1039)	-0.3215** (0.1494)	-0.3534** (0.1690)
<b>MOM</b>	-0.3339** (0.1450)	-0.2934** (0.1268)	-0.2658*** (0.1005)	-0.2961*** (0.0919)	-0.2383* (0.1316)	-0.3521** (0.1480)
<b>N</b>	515	515	515	515	516	516
<b>R-squared</b>	19.6%	19.0%	19.3%	22.4%	15.2%	18.2%

\* p<.1, \*\* p<.05, \*\*\*p<.01

Figure 10: Loser-Winner strategy returns per size group (10 Day)



Excess Returns over the look-back period of 10 days.

Figure 11: Loser-Winner strategy returns per size group (20 Day)

