Absolute Strength: Exploring Momentum in Stock Returns *

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Abstract

We document a new pattern in stock returns that we call absolute strength momentum. Stocks that have significantly increased in value in the recent past (absolute strength winners) continue to gain, and stocks that have significantly decreased in value (absolute strength losers) continue to lose in the near future. Absolute strength winner and loser portfolio breakpoints are recursively determined by the historical distribution of realized cumulative returns across time and across stocks. The historical distribution yields stable breakpoints that are always positive (negative) for the winner (loser) portfolios. As a result, winners are those that have experienced a significant upward trend, losers are those that have experienced a significant downward trend, and stocks with no momentum have cumulative returns that are not significantly different from zero. The absolute strength momentum strategy is related to, but different from, the relative strength strategy of Jegadeesh and Titman (1993). Time-series regressions show that the returns to the absolute strength momentum strategy completely explain the returns to the relative strength strategy, but not vice versa. Absolute strength momentum does not expose investors to severe crashes during crisis periods, and its profits are remarkably consistent over time. For example, an 11-1-1 strategy that buys absolute strength winners and sells absolute strength losers delivers a risk-adjusted return of 2.42% per month from 1965-2014 and 1.55% per month from 2000-2014.

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"*Lex I: Corpus omne perseverare in statu suo quiescendi vel movendi uniformiter in directum, nisi quatenus a viribus impressis cogitur statum illum mutare.*"[1]

Sir Isaac Newton (1687)

1 Introduction

Motivated by experimental and behavioral evidence (rational or irrational) on investor decisions, we investigate the extent to which absolute price changes generate predictable patterns in stock returns.[2] We find that *large* individual stock price movements in one direction over the recent past continue in the same direction in the near future. We term this pattern in stock returns "absolute strength momentum." Absolute price change classification is endogenously determined using the historical distribution of individual stock returns. At each point in time, we use the entire historical record of stock returns to classify firms into winners and losers over the ranking period, therefore using both the time series and the cross section of stock returns. Specifically, stocks with returns higher than the 90th percentile of the historical return distribution of all stocks over similar past ranking periods (absolute strength winners) earn significantly positive returns over the next period. Similarly, stocks with returns lower than the 10th percentile of the historical return distribution of all stocks over similar periods (absolute strength losers) earn negative returns over the next period.

Using the tails of the recursively updated historical return distribution of all stocks to identify absolute strength winners and losers assures that: (i) winners have positive cumulative returns and losers have negative cumulative returns over the ranking period, given the nature of the historical distribution of stock returns, (ii) the price run-up or drop over the ranking period is large enough to trigger momentum in either direction, (iii) the winner or loser classification is based on the information in the entire historical record of all firms rather than the most recent cross section, and (iv) the winner and loser return breakpoints are stable over time and, therefore, not distorted by one abnormal ranking period. The persistence in directional price movement that we uncover is reminiscent of the physics notion of momentum as the tendency of a body moving in one direction to continue moving in the same direction.[3]

[1] Also known as Newton's First Law of Motion: "Every object persists in its state of rest or uniform motion in a straight line unless it is compelled to change that state by forces impressed on it."

[2] For evidence that investors' decisions are heavily affected by absolute price changes see Kahneman and Tversky (1979), Shefrin and Statman (1985), Andreassen and Kraus (1988), Shiller (1988), DeLong, Shleifer, Summers, and Waldmann (1990), Odean (1998), Barberis and Huang (2001), Grinblatt and Han (2005), Frazzini (2006), among others.

[3] In momentum terms, we are using the historical average cumulative return of all stocks as the frame of reference in classifying stocks into positive momentum stocks (winners) and negative momentum stocks (losers). The magnitude of

We design a trading strategy that takes advantage of these extreme directional movements in stock returns. The strategy buys the stocks with the highest positive returns (absolute strength winners) and sells the stocks with the lowest negative returns (absolute strength losers) over the recent past. To be classified as an absolute strength winner (loser), a stock must have a recent cumulative return in the top (bottom) 10% of the historical cumulative return distribution. Relying on the historical return distribution naturally results in large positive cumulative return breakpoints for winners and large negative cumulative return breakpoints for losers. Using stocks that have experienced an extreme directional movement relative to the historical average increases the signal-to-noise ratio in identifying securities with true directional momentum.

The main absolute strength momentum strategy that we examine identifies stocks with extreme upward (downward) moves over the period t-12 to t-2, and tracks their performance over month t. This strategy generates a risk-adjusted return of 2.42% per month with a monthly Sharpe ratio of 0.32 from 1965 to 2014. It shows persistent profits over time including over the 2000-2014 period, which includes the recent Great Recession: its risk-adjusted return is 1.55% per month with a monthly Sharpe ratio of 0.18. The definition of what constitutes a significant upward (downward) move is stable over time with an average 64% (-43%) return for an 11-month sorting period. We uncover similar results when we vary the sorting period for cumulative returns between 3 and 12 months.

The motivation for examining a strategy that takes into account absolute strength performance comes from the notion that absolute price changes play an important role in rational and irrational investor behavior (e.g., capitals gains overhang, tax-loss selling, loss aversion, anchoring, mental accounting, and the disposition effect). Predictions of numerous behavioral models, along with experimental evidence, are consistent with the view that investors care about absolute stock price performance, and this would lead to momentum-like patterns in stock returns.[4] These models examine investors' behavior with respect to news, signals, or trends they observe for a *single* risky

the cumulative return over the ranking period can be viewed as the *speed* of movement and the sign of the cumulative return can be viewed as the *direction* of movement. Top and bottom decile breakpoints guarantee that the stocks have significant degree of movement in either direction. For comparison, Jegadeesh and Titman's (1993) relative strength momentum can be viewed as using the cross-sectional average of the ranking period cumulative returns as the frame of reference. Since the cross-sectional average changes dramatically over time, the definition of positive and negative momentum stocks can change dramatically over time.

[4]See Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), Grinblatt and Han (2005), among others. These behavioral models are among the prevalent explanations of momentum-like patterns in stock returns. Several papers have shown that momentum can also be present in markets with rational agents. These include Johnson (2002), Sagi and Seasholes (2007), Liu and Zhang (2008, 2014), Vayanos and Woolley (2013), among others.

asset. For example, a series of positive earnings surprises or positive returns would be interpreted as a period during which the stock experienced good news.

In addition, extensive experimental and survey evidence documents the importance of absolute stock performance for investors' trading decisions. For example, Shefrin and Statman (1985) and Odean (1998) document the disposition effect, which is the tendency of investors to sell the stocks that have increased in value but hold on to the stocks that have gone down in value. Frazzini (2006) argues that the disposition effect can generate stock price underreaction to news and lead to return predictability based on realized capital gains or losses. In another example, Kahneman and Tversky (1979) document that individuals are subject to loss aversion, which implies that investors become more risk averse following losses and less risk averse following gains. Barberis and Huang (2001) conclude that due to loss aversion, investors demand relatively more of an asset that has gone up versus one that has dropped in price.

Furthermore, there is evidence that some individuals tend to chase trends; they buy when prices rise and sell when prices fall, engaging in the so called positive feedback trading. For example, Andreassen and Kraus (1988) show that subjects who observe a certain price trend over a long period tend to chase the trend, buying more when prices rise and selling when prices fall. Shiller (1988) surveys investors before the 1987 market crash and finds that they tend to sell as a result of absolute price declines, presumably anticipating further price declines. Trend chasing behavior exists in the model of DeLong, Shleifer, Summers, and Waldmann (1990) where there are two types of traders. Noise traders follow positive feedback strategies - they buy when prices have risen over a certain period and sell when prices have fallen. Their demand for stocks is directly proportional to the magnitude of the price change. Rational speculators realize that it pays to jump on the bandwagon and purchase ahead of the demand from noise traders. This behavior of rational speculators further amplifies the positive feedback trading of the noise traders.

What the models mentioned above have in common is that investors' trading behavior depends on an asset's past absolute performance. In addition, the magnitude of the asset's past profit is directly proportional to the investors' demand for the stock. Finally, the models predict that stocks that have gone up in value in the recent past should continue to increase, while stocks that have gone down in value should continue to drop. Therefore, these models predict that stock returns should exhibit absolute strength momentum.

Absolute strength momentum is related to but different from the relative strength strategy studied widely in the finance literature. Relative strength momentum relies entirely on the most recent cross-sectional distribution of cumulative returns.[5] It buys assets that outperformed their peers over the recent past and shorts assets that underperformed their peers over the same period.[6] Stocks identified as past winners (losers) according to the relative strength momentum strategy have not necessarily gone up (down) in value over the ranking period for past returns. In every portfolio formation month, relative strength momentum classifies 10% of all stocks as winners and 10% of stocks as losers, regardless of the absolute magnitude and direction of their past price movement. As a result, the winner (loser) portfolio may consist of stocks that experienced a downward (upward) price movement over the recent past. It is also possible that a stock with no significant price movement could switch from the winner to the loser portfolio as a result of dramatic variation in the performance of the overall market. The following two examples convey these points in more detail.

First, over the one-year period from March 2008 to February 2009, the cumulative returns of the UMB Financial Corp, NRDC Aquisition Corp, and Corinthian Colleges Inc. were -7%, 3%, and 172%, respectively. In March 2009 all three companies were classified as relative winners based on the relative strength strategy of Jegadeesh and Titman (1993). Although all three companies outperformed 90% of all stocks over the March 2008-February 2009 period, only Corinthian Colleges Inc. was actually moving upwards, and the magnitude of the movement was large.

In another example, the cumulative return of Michigan Gas Utilities Co. over the period June

[5] One might argue that the absolute strength strategy can also be viewed as *relative* strength because winner and loser breakpoints are obtained from the return distribution that uses the entire historical record of similar period cumulative returns of all firms. However, absolute strength momentum breakpoints are remarkably stable over time, yielding positive return breakpoints for winners and negative return breakpoints for losers. The absolute strength return breakpoints resemble a filter rule such that recursively updated filters are endogenously determined from publicly available historical data.

[6] Jegadeesh and Titman (1993) first show that relative strength momentum is profitable in the cross section of US stocks: past relative winners continue to outperform past relative losers in the near future. Relative strength momentum is one of the strongest and most puzzling asset pricing anomalies. Numerous papers have verified that relative strength momentum exists not only in U.S. stocks, but also in industries (Moskowitz and Grinblatt (1999)), foreign stocks (Rouwenhorst (1998), Griffin, Ji, and Martin (2003)), equity indices (Asness, Liew, and Stevens (1997), Bhojraj and Swaminathan (2006), Hvidkjaer (2006)), commodities (Pirrong (2005), Miffre and Rallis (2007)), currencies (Menkoff et al (2011)), global government bonds (Asness, Moskowitz, and Pedersen (2012)), and corporate bonds (Jostova, Nikolova, Philipov, and Stahel (2010)). However, despite its early success, some recent evidence present significant challenges to relative strength momentum. First, Novy-Marx (2012) shows that an asset's relative performance over the first half of the preceding year seems to better predict returns compared to its relative performance over the most recent past. This evidence implies that there is an "echo" in returns rather than "momentum." Second, Daniel and Moskowitz (2014) document that there are times when relative strength momentum experiences severe crashes that can significantly reduce the accumulated gains from the strategy. Finally, relative strength momentum profits seem to have declined and become insignificant over the most recent period since 2000. This combined evidence brings into question the continued profitability and persistence of relative strength momentum.

1969-April 1970 was 0.4%. This return was in the top 10% of the distribution of cumulative returns over that period. Therefore, in May 1970, Michigan Gas Utilities Co. would have been classified as a past winner according to the relative strength momentum strategy. Subsequently, the cumulative return of Michigan Gas Utilities Co. over the period July 1970-May 1971 was 0.6%. This return was in the bottom 10% of the distribution of cumulative returns over that period. Therefore, in June 1971, Michigan Gas Utilities Co. would have been classified as a past loser according to the relative strength momentum strategy. It seems that over a period of approximately two years, the price of Michigan Gas Utilities Co. did not reflect any news and remained stable resulting in a cumulative return of about 0%. However, the relative strength momentum characteristic of the stock varied dramatically from one extreme to the other.

In contrast, absolute strength momentum combines information from the most recent distribution of cumulative returns with information from the historical distribution of cumulative returns. For example, although the 3% cumulative return of NRDC Aquisition Corp over the period from March 2008 to February 2009 is positive, its performance does not place in the top 10% of the historical distribution which is defined by a return higher than 66% for an 11-month sorting period in March 2009. Therefore, NRDC Aquisition Corp does not qualify as an absolute strength winner in March 2009. On the other hand, the 172% cumulative return of Corinthian Colleges Inc over March 2008 to February 2009 qualifies it to be included in an absolute strength winner portfolio.

The key innovation of the absolute strength momentum strategy is the use of consistent thresholds in classifying stocks into winners and losers. These consistent breakpoints naturally arise from the use of the historical distribution of cumulative returns.[7] Specifically, at the beginning of each month t, we compute the cumulative returns of all stocks over the period t-12 to t-2.[8] To determine whether these cumulative returns are high or low, we look at the distribution of all previous non-overlapping 11-month cumulative returns. For example, at the beginning of January, we record cumulative returns for all stocks over the period from last January to last November. These returns are ranked on the basis of the historical distribution of January to

[7]The recursive data-driven approach in deriving return breakpoints helps avoid look-ahead bias in identifying winners and losers. The approach mimics the behavior of an investor who learns what winners and losers look like historically before forming winner and loser portfolios based on the most recent data. The investor then updates her beliefs every month as new data becomes available.

[8]Skipping a month between the ranking period for cumulative returns and the holding period is common in the literature. It is used in order to avoid the short-term reversal effect documented by Jegadeesh (1990) and Lehman (1990), among others. Our choice of 11-1-1 as the main strategy is motivated by its recent popularity. We also consider other strategies with different ranking and holding periods as in Jegadeesh and Titman (1993). In addition, we consider strategies that do not skip a month between the ranking and holding period, and strategies that skip a week. In all cases, results are similar to the results reported in the main empirical analysis.

November cumulative returns of all stocks in all times. If a stock's cumulative return over t-12 to t-2 falls in the top (bottom) 10% of the historical distribution, we classify that stock as an absolute winner (loser). We repeat this process every month. Therefore, our return breakpoints assure that an absolute winner is an asset that has done well over the recent 11 months according to the historical record. Similarly, an absolute loser is an asset that has done poorly over the recent 11 months according to the historical record. Therefore, each month we effectively compare the distribution of cumulative stock returns over the recent past to the historical distribution of 11-month cumulative stock returns.

A defining feature of the absolute strength momentum strategy is that it does not impose the requirement that there should always be some stocks designated as winners or losers. For example, there are instances in which none of the stocks meet the criteria to be defined as absolute strength winners or losers. Due to this feature of absolute strength momentum, the stocks identified as absolute strength winners or losers are not simply a smaller subset of the stocks defined as relative strength winners or losers. That is, the absolute strength momentum strategy does not achieve its profits simply by trading in stocks with more extreme past returns. Often times, absolute strength momentum invests in different assets from relative strength momentum. To implement the absolute strength momentum strategy, we require that both the absolute strength winner and loser portfolios have an adequate number of firms for a hedge strategy. We argue that this is represented by 30 stocks. If, in a given month, there are not enough firms in either the absolute strength winner or loser portfolio to implement a hedge strategy, then we invest in the one-month T-bill. In these months, the absolute strength strategy signals that the market went too far in one direction and there is no momentum in the other leg, signaling an impending momentum crash.

We show that the absolute strength momentum strategy not only does well over various sample periods, but also has several interesting features that distinguish it from relative strength momentum. For example, absolute strength momentum does not suffer from the "echo" effect which exists in relative strength momentum as documented by Novy-Marx (2012).[9] We show that intermediate horizon absolute strength and recent absolute strength performance contribute equally to the predictability of future performance. Furthermore, the absolute strength momentum strategy is not subject to the severe crashes observed for relative strength momentum. More importantly, we show that we are able to reliably predict and avoid crash periods in real time by following absolute strength momentum rules. Using time-series regressions, we also document that the returns to

[9] Goyal and Wahal (2013) find mixed evidence for the "echo" effect in 37 countries, excluding the U.S.

the relative strength momentum strategy are completely explained by the returns to the absolute strength momentum strategy, but not vice versa.

To understand the relation between absolute strength and relative strength momentum, we decompose the returns to relative strength momentum following the framework of Lo and Mackinlay (1990) and Lewellen (2002). This decomposition allows us to identify the properties of returns that contribute to relative strength momentum. We show that relative strength momentum has similar performance to absolute strength momentum at times when the distribution of cumulative stock returns over the most recent 11 months is similar to the historical distribution of 11-month cumulative stock returns. Whenever the distribution of cumulative stock returns over the most recent 11 months deviates from the historical distribution of 11-month cumulative stock returns, the relative strength momentum strategy is not profitable. This result suggests that the superior performance of absolute strength momentum could also be viewed as a way to better time the relative strength momentum strategy.

Finally, we compare the performance of absolute strength momentum to another strategy that buys stocks with positive excess returns and sells stocks with negative excess returns over the ranking period. This strategy focuses on a security's own past return rather than its relative return and so it is different from relative strength momentum. It is related to the time series momentum strategy of Moskowitz, Ooi, and Pedersen (2012), who show that buying assets classes with positive excess returns and selling asset classes with negative excess returns over a ranking period generates significant profits. Our time series momentum strategy complements the one examined by Moskowitz, Ooi, and Pedersen (2012) since we use individual stocks rather than asset classes such as equity indices, bonds, commodity futures, or currencies. The time series momentum strategy with individual stocks is different from our absolute strength momentum strategy, which focuses on large and significant price movements in the positive or negative direction. As the Michigan Gas example above suggested, using zero or the risk-free rate as the return breakpoint to distinguish winners from losers (as time series momentum does), populates the winner and loser portfolios with stocks that have near zero returns. This reduces the signal to noise ratio of the momentum strategy significantly. Using time-series regressions, we show that absolute strength momentum completely explains the returns to time series momentum, but not vice versa.

The fact that stocks with significant movement in either direction have considerably higher momentum than stocks with near zero returns (which make up the majority of stocks in the time series momentum portfolios), suggests a possible explanation for the profitability of our absolute strength momentum strategy. We show that classifying stocks into absolute strength winners (losers) but not time series winners (losers) identifies stocks with large unrealized capital gains (losses) as measured by the capital gains overhang used in Frazzini (2006). The capital gains overhang measures the extent to which the stock has appreciated (depreciated) since purchase. The disposition effect predicts that investors' decisions to buy or sell crucially depend on the purchase price of the stock. To the extent that the disposition effect drives the profitability of momentum, as suggested by Grinblatt and Han (2005), a recent significant upward (downward) move in the stock price is more likely to place the stock in the disposition-effect-induced trading category for most investors.

The remainder of the paper proceeds as follows. Section 2 describes how the absolute strength momentum strategy is constructed, examines its characteristics, and reports its performance over different sample periods. Section 3 examines in detail the commonalities and differences between absolute strength momentum and relative strength momentum. Section 4 examines the relation between absolute strength momentum and the time series momentum strategy that uses individual stocks. Section 5 offers several robustness checks and Section 6 concludes.

2 Absolute Strength Momentum Strategy

2.1 Data and Absolute Strength Return Breakpoints

To construct our main sample, we use only common stocks traded on the NYSE, AMEX, and NASDAQ. Stock market data comes from CRSP. At the beginning of each month t, we compute the cumulative returns of all firms from month t-12 to t-2. Stocks priced below $1 at the beginning of the holding period are excluded. Firms must have at least eight return observations in the t-12 to t-2 window.

One way to judge whether the 11-month cumulative return of a stock makes it a winner or a loser is to compare the performance of the stock to that of all other stocks over the recent 11-month period. For example, in April 2009, a stock with a past 11-month return of negative 5% is classified as a winner, relative to the performance of all other stocks over the same period. This argument ignores all other information about the past performance of stocks over previous 11-month intervals. However, for an investor who incorporates historical information about stock performance in her decisions, it is difficult to associate a return of negative 5% with a winning investment. In April

2009, based on historical information about previously realized 11-month returns, this stock would not have placed in the top 10% of the historical distribution (a 66% return). Therefore, when the stock's return over the last 11 months is compared to what constitutes a positive performance over an 11-month interval based on the historical benchmark, a stock with a negative 5% return becomes an absolute loser. The term "absolute" refers to the point that the stock is being evaluated relative to the historical benchmark which is stable over time. The strength of the negative momentum experienced by the stock over the recent 11-month period could also be determined based on historical performance. A return of negative 5% does not qualify as a strong negative momentum according to the historical benchmark. We argue that adding historical perspective to the most recent 11-month distribution of returns provides useful information for the future performance of stock returns.

We propose that in order to determine return breakpoints for absolute strength winners or losers at time t, we should look at the historical information about returns using all available data prior to month t. Specifically, at the beginning of each month t, we compute the cumulative returns of all stocks over the period t-12 to t-2. To determine whether these cumulative returns are high or low, we look at the distribution of all previous non-overlapping 11-month cumulative returns. For example, at the end of December, we record cumulative returns for all stocks over the period from the preceding January to November. These returns are ranked on the basis of the historical distribution of January to November cumulative returns. If a stock's cumulative return over t-12 to t-2 falls in the top (bottom) 10% of the historical distribution, we classify that stock as an absolute strength winner (loser). We repeat this process every month. Therefore, the historical distribution of 11-month cumulative returns is updated continuously.

Figure 1 plots the absolute strength winner and loser cumulative return breakpoints based on the method described above, from January 1965 to December 2014. Even though we start the analysis in 1965, we use return data back to 1927 to determine performance breakpoints. At the beginning of the sample, the 11-month absolute strength winner cutoff starts approximately at a 60% return, and by the end of the sample, it is updated up to an approximate 70% return. The absolute strength loser cutoff starts with an approximate -30% return and is updated down to an approximate -50% return by the end of the sample period. Even though both cutoffs display slight variation, the definition of an absolute strength winner or loser is relatively stable over time.[10]

[10] There is seasonality in the breakpoints displayed in Figure 1. The seasonality is due to the different 11-month windows used to compute cumulative returns every month. It turns out that both the absolute strength winner and

Furthermore, using the historical distribution naturally leads to an absolute strength winner (loser) breakpoint that is always positive (negative). Stocks identified as absolute strength winners (losers) according to the new momentum breakpoints have been increasing (decreasing) in value before portfolio formation.

The absolute strength winner (loser) breakpoints that we derive resemble a filter rule. Figure 1 suggests that stocks are defined as absolute strength winners or losers if the level of their 11-month cumulative return is outside specific filter breakpoints.[11] A stock is included in the absolute strength winner (loser) portfolio only if its 11-month cumulative return moved up (down) by a specific amount. However, in contrast to filter rules, the breakpoints that we derive are not exogenously pre-determined and are time-varying. They are data-driven since we let historical performance dictate what is an absolute strength winner (loser). This helps us avoid a look-ahead bias in the determination of absolute strength return breakpoints.

It is interesting to contrast the cumulative return breakpoints derived above with the ones derived by the relative strength momentum strategy. Figure 2 plots winner and loser cumulative return breakpoints for relative strength momentum from January 1965 to December 2014. To compare, we also plot cumulative return breakpoints for absolute strength winners and losers on the same graph. The plot shows that relative strength return breakpoints vary dramatically over time. For example, the relative loser breakpoint varies from a minimum of -87% return to a maximum of 10% return. The relative winner breakpoint varies from a minimum of -10% return to a maximum of 250% return. Therefore, the definition of relative winners (losers) is not constant over time. Furthermore, the relative loser breakpoint is positive in 15 months of the sample, while the relative winner breakpoint is negative in eight months. Clearly there are times when all stocks identified as relative winners (losers) have been decreasing (increasing) in value before portfolio formation.

Figure 2 also shows that absolute winners (losers) are not merely a smaller subset of relative winners (losers). For example, during the recent Great Recession, the absolute loser breakpoint was smaller in magnitude than the relative loser breakpoint. Therefore, some absolute losers do not

loser breakpoints are lowest for the January to November 11-month window, which produces the lowest cumulative returns historically (the absolute strength winner (loser) breakpoint is 60% (-49%) on average in January vs. an overall average of 68% (-43%)). The lower return breakpoints over January-November are probably due to the fact that the January to November window excludes December which is the month with the best average performance for the overall market. In the Appendix, we show that when the historical distribution of returns is based on overlapping 11-month windows, the corresponding return breakpoints are smoother.

[11] Cooper (1999) uses filter rules on lagged stocks returns to examine security overreaction. He defines stocks as winners or losers if their recent returns are within specific filter breakpoints.

qualify as relative losers. Similarly, in some periods after the Great Recession, the absolute winner breakpoint is lower than the relative winner breakpoint. This indicates that not all absolute winners are relative winners. Therefore, the profitability of the absolute strength momentum strategy is not driven by trading in stocks with more extreme past returns. Untabulated results show that the average cumulative returns over the ranking period of absolute strength winners and relative strength winners are similar (108% vs 115%, respectively). Similarly, the average cumulative returns over the ranking period of absolute strength losers and relative strength losers are similar (-53% vs -47%, respectively).[12] Clearly, the two momentum strategies contain different stocks on average in their winner (loser) portfolios.

2.2 Number of Firms

After absolute strength performance breakpoints are identified every month, we sort stocks into 10 value-weighted portfolios based on their cumulative returns during the past 11 months. The portfolios are based on each 10th percentile of the historical distribution of past returns. These portfolios are held for one month and are then rebalanced. Following previous studies, we skip one month between the ranking period for cumulative returns and the start of the portfolio holding period. This method avoids the one-month reversal effect documented by Jegadeesh (1990) and Lehmann (1990).[13] We also evaluate the performance of the absolute strength momentum strategy that buys absolute strength winners and sells absolute strength losers. The absolute strength winners (losers) are based on the 90th (10th) percentile of the historical distribution of past returns.

A key feature of the absolute strength momentum strategy is that it does not impose the requirement that there should always be some stocks designated as winners or losers. This is because performance breakpoints are based on the historical rather than the most recent distribution of returns. Therefore, there might be instances in which the absolute strength winner or loser portfolios are not populated by any stocks. Figure 3 plots the number of firms in the absolute strength winner and loser portfolios over time. The figure shows that there are times when few firms qualify to be

[12] Bandarchuk and Hilscher (2012) show that sorting stocks on certain stock-level characteristics (size, turnover, analyst coverage, analyst forecast dispersion, book-to-market, liquidity, credit rating) and then on past returns results in higher momentum profits by identifying stocks with more extreme past returns. Given that absolute and relative strength winners (losers) have similar average ranking period returns, the absolute strength performance of a stock cannot be viewed as yet another stock characteristic that identifies more extreme past returns.

[13] The relative strength momentum strategy that sorts stocks on their 11-month past return, skips a month, and then holds the stocks for one month is examined by Fama and French (1996) and others. Jegadeesh and Titman (1993) examine relative strength momentum strategies that sort stocks on their 3-, 6-, 9-, or 12-month past returns and hold them for 3, 6, 9, or 12 months after portfolio formation. The main strategy that we examine focuses on a 11-month sorting period and 1-month holding period. Later we present results for other strategies.

in the absolute strength winner or loser portfolios. For example, in January 2009, only 24 stocks qualify to be classified as absolute strength winners based on their cumulative returns from January 2008 to November 2008. In April 2004, only 18 stocks qualify to be classified as absolute strength losers.

When one leg of the absolute strength momentum strategy has very few firms, the other leg naturally has a large number of firms. For example, when either the long or the short leg of the hedge portfolio has fewer than 30 stocks (16 on average), the other leg has 917 stocks on average. To make sure that the strategy has a practical relevance and we are not documenting just paper profits, we require that either the long or the short leg has at least 30 stocks.[14] We estimate that a minimum of 30 stocks can support an investment of about $1 million without adversely affecting prices due to transaction costs.[15]

At each point in time, the number of absolute strength winners (losers) identified by absolute strength momentum differs from the number of relative strength winners (losers) identified by relative strength momentum. Each month, the relative performance classification partitions the universe of stocks into 10 value-weighted portfolios with an equal number of stocks in each portfolio.[16] Therefore, relative winner and loser portfolios are always populated by stocks that fit the relative performance breakpoints. This feature of relative strength momentum makes its performance significantly tied to the performance of the overall market. If the market has fallen significantly over the sorting period, chances are that relative winners (losers) are low (high) beta firms. Therefore, following market declines, the relative momentum portfolio is likely to be long low-beta stocks and short high-beta stocks. If the market rebounds quickly following a decline, relative strength momentum will crash due to its conditionally large negative beta.[17] We show

[14]Computing portfolio return based on 30 stocks or more mitigates concerns about the return being driven by outliers.

[15]We assume that a stock investment of 5% of daily dollar volume is the maximum that can be implemented without moving the price of the stock. The median daily dollar volume in our sample is $709,821. Based on this, 30 stocks can support an investment of about $1 million with minimal price impact. In addition, Statman (1987) argues that to achieve a well-diversified portfolio, approximately 30 stocks are needed. Finally, transaction cost concerns aside, an adequate number of stocks are needed in each leg to achieve a sufficient degree of industry and market neutrality for the hedge strategy. Having said that, our results are not sensitive to choosing 30 as the minimum number of stocks required in the absolute strength winner/loser portfolio. With the 30 stocks condition, the absolute strength momentum strategy is able to avoid 45% of the crash months in the sample (defined as months in which the return to relative strength momentum is less than -20%) and its Sharpe ratio is 0.32. We have performed an experiment where we vary the number of stocks required as a minimum in the absolute strength winner/loser portfolio from 10 to 100. The results show that the percentage of crashes avoided by the resulting absolute strength momentum strategy varies from 32% to 73% and the Sharpe ratio of the strategy varies from 0.30 to 0.32.

[16]The number of stocks in each portfolio might differ slightly if a price filter is imposed on the data.

[17]Kothari and Shanken (1992) first document the time variation in betas of portfolios sorted by past relative performance. Grundy and Martin (2001) and Daniel and Moskowitz (2014) also study time variation in the market

that the absolute strength momentum strategy is able to avoid the significant crashes that are documented for relative strength momentum.

2.3 Performance

Table 1 presents monthly characteristics for ten portfolios sorted by absolute strength performance. Portfolios 1 through 10 correspond to decile performance breakpoints based on the historical distribution of returns. The table presents summary statistics for each performance breakpoint. The absolute strength winner (loser) breakpoint is always positive (negative) and all breakpoints show remarkable stability over time. Portfolio characteristics are measured monthly and include average return and its t-statistic, average excess return, volatility, Fama-French (1993) alpha, market beta, and Sharpe ratio.[18] The strategy that buys absolute strength winners and sells absolute strength losers is presented in the last column. The table shows that absolute strength winners continue to gain, while absolute strength losers continue to lose. This is consistent with the presence of absolute strength momentum in stock returns. Furthermore, the absolute strength momentum strategy generates significant profits of 2.16% per month for the period 1965-2014 and 1.51% per month for the period 2000-2014.

The risk-adjusted returns of the portfolios also show that stocks that have been increasing (decreasing) in value in the recent past continue to increase (decrease) in value after portfolio formation. The absolute strength momentum strategy generates significant risk-adjusted returns of 2.42% per month for the period 1965-2014 and 1.55% per month for the period 2000-2014. The period from 2000 to 2014 is noteworthy since it includes the recent Great Recession. The results indicate that the absolute strength momentum strategy was profitable, on average, during the period that includes the worst recession in recent memory.

For comparison, Table 2 presents monthly characteristics for ten portfolios sorted by relative strength performance. The table also shows summary statistics for each relative performance breakpoint. The relative strength winner (loser) breakpoint is sometimes negative (positive) and all breakpoints show substantial variation over time. The table shows that the relative strength momentum strategy is also profitable in the period 1965-2014. However, its performance is worse than the performance of absolute strength momentum described in Table 1. Furthermore, in

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betas of relative strength momentum portfolios. Daniel and Moskowitz (2014) document that the negative beta of relative strength momentum is related to the severe momentum crashes they document.

[18] The characteristics are computed over the months during which both portfolios 1 and 10 consist of at least 30 stocks.

contrast to absolute strength momentum, from 2000 to 2014, relative strength momentum does not produce significant profits. The Sharpe ratio of relative strength momentum is smaller than the Sharpe ratio of absolute strength momentum in both sample periods that we examine in Table 2. Interestingly, the market beta of absolute strength momentum is less than half the size of the market beta of relative strength momentum.

Figure 4, Panel A, plots the cumulative monthly log returns from investing $1 in absolute strength momentum during 1965-2014. For comparison, we also plot the cumulative monthly log returns for investments in relative strength momentum, the risk-free asset, and the market. The final dollar amounts for each strategy at the end of 2014 are presented on the right side of the plot. For absolute strength momentum, $1 invested at the beginning of 1965 grows to $96,236 at the end of 2014. For relative strength momentum, $1 appreciates to $6,127. Both investments do better than holding the risk-free asset or the market alone.

Relative strength momentum experiences a large drop in accumulated wealth during the first half of 2009, which corresponds to the period of the recent Great Recession. Absolute strength momentum, on the other hand, is able to do better during that time period and does not experience a large drop in value. In order to examine the period around the Great Recession in more detail, we plot the cumulative monthly log returns for investing $1 in relative strength momentum, absolute strength momentum, the risk-free asset, and the market for the period 2000-2014. Panel B of Figure 4 shows that over March and April of 2009, the relative strength momentum strategy loses approximately 50% of its accumulated value and by the end of the sample period, there is no appreciation in the $1 invested in the strategy. In contrast, absolute strength momentum does not lose much value during the Great Recession, and there is substantial appreciation in its return during 2000-2014.

3 Absolute Strength vs. Relative Strength Momentum

Our previous results show that absolute strength momentum and relative strength momentum are related since they focus on recent stock performance. However, the two strategies provide different interpretations of the strength of the most recent stock performance. In this section, we examine the relation between absolute and relative strength momentum in more detail. The goal is to determine what drives the difference between the two strategies.

3.1 Absolute Strength Momentum Regressed on Relative Strength Momentum

If relative strength momentum completely captures absolute strength momentum, then we would expect to see a zero intercept in a time-series regression in which the dependent variable is absolute strength momentum. Table 3 presents results from a time-series regression for the period 1965-2014 in which the dependent variable is the return of the absolute strength momentum strategy and the independent variable is the return of the relative strength momentum strategy. To account for the presence of other factors that might explain the behavior of the absolute strength momentum strategy, we control for the market portfolio and the Fama-French (1993) value and size factors in another specification.

The results in Table 3 show that absolute strength momentum loads significantly on relative strength momentum. This reflects the fact that the strategies are highly correlated (74%). However, the time-series intercepts in both specifications are significantly positive and, at 1% per month, are also economically large. Therefore, the absolute strength momentum strategy contains information which is not subsumed by the relative strength momentum strategy.

We also consider the case in which the dependent variable is relative strength momentum and the independent variables are absolute strength momentum or the excess market return, HML, SMB, and absolute strength momentum. The results in Table 3 reveal that relative strength momentum is significantly exposed to absolute strength momentum. Furthermore, the time-series intercept in either specification is not significant, and its economic magnitude is negligible. Therefore, the results suggest that the returns to relative strength momentum are completely explained by absolute strength momentum.

In summary, absolute strength momentum subsumes the information contained in relative strength momentum. However, the reverse does not hold. Absolute strength and relative strength momentum are different. Absolute strength momentum represents a new pattern in returns that cannot be explained by conventional factors.

3.2 Is Absolute Strength Momentum Really Momentum?

A recent paper by Novy-Marx (2012) shows that relative strength momentum portfolios formed on the basis of returns from 12 to seven months prior to portfolio formation (intermediate horizon returns, denoted as IR) have substantially higher profits than relative strength momentum portfolios formed based on returns from six to two months prior to portfolio formation (recent horizon returns, denoted as RR). Therefore, intermediate horizon relative performance, not recent relative performance, seems to predict future performance. Novy-Marx (2012) points out that this is inconsistent with the traditional view of momentum that rising stocks keep rising, while falling stocks keep falling. These results represent a significant challenge to the relative strength momentum strategy since they suggest that there is an "echo" effect in stock returns rather than a relative momentum effect.

In this section we first replicate Novy-Marx's (2012) results in our sample. Second, we test whether the "echo" effect exists when stocks are sorted based on intermediate horizon absolute strength and recent absolute strength performance.

To replicate Novy-Marx's (2012) results, we compute two types of rankings for each stock. First, we compute the relative performance of the stock from 12 to seven months prior to portfolio formation and assign it a ranking from IR1 (loser) to IR5 (winner). Second, we compute the relative performance of each stock from six to two months prior to portfolio formation and assign it a ranking from RR1 (loser) to RR5 (winner). We then form value-weighted portfolios of stocks in each category. We exclude stocks that are priced below $1 at the beginning of the holding period. Table 4 reports the average monthly returns of these portfolios. It also reports the returns of buying relative winners and selling relative losers in each group of relative performance. The table shows that for the sample period 1965 to 2014, using relative strength momentum strategies, the echo effect in returns first uncovered by Novy-Marx (2012) is still present. The profits associated with the RR momentum strategy represent approximately 50% of the profits generated by the IR momentum strategy. These results suggest that the "echo" effect in returns is stronger than the relative strength momentum effect.

Since the two ranking periods for returns in Novy-Marx (2012) span a period of 11 months, we propose a possible explanation of his findings based on the existence of absolute strength momentum. We hypothesize that if a stock is a relative winner over t-12 to t-7, but the same stock is a relative loser over t-6 to t-2, then this stock will not be an absolute winner (or loser) over t-12 to t-2. In other words, when the stock is not consistently in the relative winner (or loser) category both in the intermediate term and the short term, then it will not have absolute strength momentum over the last 11 months. To test this, we compute the 11-month absolute strength ranks of the portfolios double-sorted on relative IR and RR. The results are presented in Table 5.

Table 5 shows that in each RR group, the 11-month absolute strength rank increases as the IR rank of the portfolio increases. Similarly, in each IR group, the 11-month absolute strength rank increases as the RR rank of the portfolio increases. Portfolios that are both IR and RR losers or both IR and RR winners also tend to be 11-month absolute strength losers or winners, respectively. Not surprisingly, the highest return spread in Table 4 comes from going long in portfolio RR5/IR5 and going short in portfolio RR1/IR1. Table 5 also reports the relative strength 11-month ranks of the portfolios. The results are similar to the ones reported for absolute strength ranks.

Next, we examine whether the "echo" effect is an issue for absolute strength momentum. That is, we test whether intermediate absolute strength performance subsumes the effect of recent absolute strength performance on future returns. We compute two types of rankings for each stock. The first ranking is the absolute strength IR ranking for the period t-12 to t-7. The approach we use is similar to the one used for 11-month cumulative returns. Second, we compute the absolute strength performance of each stock from t-6 to t-2. Stocks are assigned to 25 portfolios based on their absolute strength IR and RR ranking. Table 6 reports the average monthly returns of these portfolios. It also reports the returns of buying absolute strength winners and selling absolute strength losers in each group of intermediate and recent performance. The table shows that absolute strength IR and absolute strength RR are equally important in predicting future returns. Overall, the results suggest that absolute strength momentum is robust to the "echo" effect in returns first documented by Novy-Marx (2012) in the context of relative strength momentum.

According to Novy-Marx (2012), the term momentum, which is the tendency of a body in motion to stay in motion, is not consistent with buying relative strength winners and selling relative strength losers. In contrast, we show that the physics notion of momentum accurately describes the returns to buying absolute strength winners and selling absolute strength losers.

3.3 Momentum Crashes

Daniel and Moskowitz (2014) show that the relative strength momentum strategy based on performance from 12 to two months before portfolio formation comes with occasional large crashes. For example, during the two worst months for the strategy, July and August of 1932, the relative strength loser portfolio returned 236%, while the relative strength winner portfolio returned 30%. More recently, from March 2009 to May 2009, the relative strength loser portfolio rose 156%, while the relative strength winner portfolio gained only 6.5%. These sudden crashes of relative strength momentum take decades to recover from, and the large average returns of the strategy might not be enough to compensate investors for being exposed to this risk.

In Table 7, Panel A, we report the worst monthly returns (in %) for the relative strength momentum strategy. To make our results directly comparable to Daniel and Moskowitz (2014), we have extended the sample back to 1927. We also report the number of firms in the relative strength loser and winner portfolios. In addition, the table reports the monthly returns of absolute strength momentum during the worst months of relative strength momentum, and the number of firms in the absolute strength winner and loser portfolios. The table shows that, by construction, the relative strength winner and loser portfolios have large number of firms in both legs even during the worst months for the strategy. However, the absolute strength winner and loser portfolios are not always populated. For example, in July 1932, the absolute strength winner portfolio contains only two stocks. Or, in September 1939, the absolute strength loser portfolio contains only five stocks, while the absolute strength winner portfolio contains only 25 stocks. In months like these, we hold the risk-free asset since absolute strength momentum cannot be reliably implemented.

Panel A of Table 7 also shows that during the months in which both strategies are implementable, the crashes of absolute strength momentum are smaller in magnitude than the ones for relative strength momentum. In those months, the absolute strength loser portfolio contains many more stocks than the relative strength loser portfolio. The smaller crashes of absolute strength momentum are consistent with the strategy having a much lower market beta than relative strength momentum (see Tables 1 and 2).

In Panel B of Table 7, we report the worst monthly returns (in %) for the absolute strength momentum strategy. The results show that, for the most part, absolute strength momentum "crashes" at different times than relative strength momentum. Two other observations stand out. First, unconditionally, the largest crashes of absolute strength momentum are much smaller than those of relative strength momentum (e.g., -39% vs. -78%). Second, conditional on absolute strength momentum experiencing a crash, the returns of relative strength momentum still tend to be lower.

We argue that our new method of identifying absolute strength winner and loser stocks provides a reliable way of predicting impending crashes for relative strength momentum. Absolute strength momentum is able to avoid the worst crashes of relative strength momentum. The reason for this is that we require that both absolute strength winner and loser portfolios have an adequate number of firms to be implementable. The data shows that absolute strength winner portfolios tend to contain few stocks in crisis periods. When the overall market has experienced a substantial drop (increase) in value, it is difficult to find assets that look like absolute winners (losers). If there are not enough stocks to qualify as absolute strength winners (or losers), our strategy indicates a switch to the risk-free asset.[19]

The number of stocks in the absolute strength winner (or loser) portfolio acts as an indicator variable for states of the world in which the overall market is experiencing unusual price movements. Motivated by this observation, we examine in more detail the performance of relative and absolute strength momentum in states of the world in which the absolute winner/loser portfolios are and are not implemented. Table 8 presents the results for the main sample period from January 1965 to December 2014. In 25 months of this sample period, there are less than 30 absolute strength losers. The average return of absolute (relative) strength momentum is 0.53% (0.45%) per month. The return of absolute strength momentum comes from holding the risk-free asset. Table 8 shows that in 27 months there are less than 30 absolute strength winners. The average return of absolute (relative) strength momentum over these months is 0.49% (-0.73%) per month. Therefore, relative strength momentum has lower profits than absolute strength momentum in states when the absolute strength loser or winner portfolios are not well-diversified. The last column of Table 8 shows the performance of the two momentum strategies in the states when the absolute strength loser and winner portfolios are well-diversified. In 548 months there are at least 30 absolute strength losers and winners. The average return of absolute (relative) strength momentum over these months is 2.32% (2.04%) per month, with a Sharpe ratio of 0.32 (0.23). Therefore, absolute strength momentum outperforms relative strength momentum in different states of the world.

3.4 A Simple Decomposition

In this section, we follow the method of Lo and Mackinlay (1990) and Lewellen (2002) to write a simple relation between absolute strength and relative strength momentum. To make the comparison easier, we examine strategies that invest in all available stocks. For relative strength momentum, we let the portfolio weight of stock i be $w_{i,t}^{RS} = (1/N) * (r_{i,t-12,t-2} - r_{t-12,t-2}^{EW})$, where $r_{t-12,t-2}^{EW}$ is the equal-weighted average cumulative return over t-12 to t-2. The return to relative

[19] We also construct an absolute strength momentum portfolio that invests in stocks from other deciles if there are not enough stocks to qualify as absolute strength winners or losers. For example, if the absolute strength decile 10 contains only 10 stocks, we move on to decile 9 to find more absolute winners. We follow this search method until we are able to find at least 50 stocks that are absolute winners. A similar method is applied to the short leg of the strategy. Untabulated results show that this alternative absolute strength momentum strategy experiences less severe crashes and has an overall higher average return than relative strength momentum. These results are available upon request.

strength momentum is therefore:

$$r_{t,t+1}^{RS} = \sum_{i=1}^{N} w_{i,t}^{RS} * r_{i,t,t+1}. \tag{1}$$

Similarly, for absolute strength momentum, we let the portfolio weight of stock i be $w_{i,t}^{AS} = (1/N) * (r_{i,t-12,t-2} - r_{H,t})$, where $r_{H,t}$ is the historical average cumulative return over 11-month intervals. It has a time subscript since it is being updated each month as new information becomes available. The return to absolute strength momentum is therefore:

$$r_{t,t+1}^{AS} = \sum_{i=1}^{N} w_{i,t}^{AS} * r_{i,t,t+1}. \tag{2}$$

Combining Equations (1) and (2), we show that:

$$\begin{aligned} r_{t,t+1}^{RS} &= \sum_{i=1}^{N} (1/N) * [(r_{i,t-12,t-2} - r_{H,t}) - (r_{t-12,t-2}^{EW} - r_{H,t})] * r_{i,t,t+1} \\ &= \sum_{i=1}^{N} (1/N) * [(r_{i,t-12,t-2} - r_{H,t}) - (r_{t-12,t-2}^{EW} - r_{H,t})] * r_{i,t,t+1} \\ &= r_{t,t+1}^{AS} - \sum_{i=1}^{N} (1/N) * (r_{t-12,t-2}^{EW} - r_{H,t}) * r_{i,t,t+1}. \end{aligned} \tag{3}$$

According to the setup in Equation (3), the relative strength momentum portfolio has a long position in the absolute strength momentum portfolio and a short position in a portfolio that assigns positive (negative) weights to all stocks when the recent average cumulative return is higher (lower) than the historical average cumulative return. Untabulated results show that the average return of this second portfolio is positive over the period 1965-2014. Therefore, absolute strength momentum outperforms relative strength momentum. This is consistent with our previous results that use the extreme deciles of each momentum strategy.

Equation (3) shows that if the recent average cumulative return is close to the historical average cumulative return, the profits to relative strength and absolute strength momentum will be similar. When there is a substantial difference between the averages of the recent and the historical distribution of cumulative returns, the profits to the two momentum strategies will differ as well. In the setup used here, the difference in the profits between the two momentum strategies is driven by the different weights they assign to all securities. At times when the recent average cumulative return is greater than the historical average cumulative return, relative strength momentum assigns smaller (higher) weights to stocks that are absolute winners (losers) than absolute strength momentum. At times when the recent average cumulative return is smaller than the historical average cumulative return, relative strength momentum assigns higher (smaller) weights to stocks that are absolute winners (losers) than absolute strength momentum.

Our previous results reveal that when there is a substantial difference between the averages of the recent and the historical distribution of cumulative returns (i.e., following significant up or down movements by the overall market), few of the firms in the market fit the absolute strength winner or loser criteria. Combined with the intuition from Equation (3), this suggests that following the rules of the absolute strength momentum strategy could be viewed as a way of timing the relative strength momentum strategy. For example, such timing would suggest that relative strength momentum should not be implemented at times when very few firms (< 30) are absolute strength winners or losers. During such times, the distribution of recent 11-month cumulative returns differs substantially from the historical distribution of 11-month cumulative returns.

To test this timing hypothesis, we construct a measure called *diff*, which captures the difference at each point in time between the median of the distribution of recent 11-month cumulative returns and the median of the historical distribution of 11-month cumulative returns.[20] We propose that the absolute value of *diff* is a factor behind the predictability of future returns based on recent 11-month cumulative returns.

More specifically, the γ_1 coefficient in the following cross-sectional regression captures the predictability of future returns based on past returns:

$$r_{i,t} = \gamma_0 + \gamma_1 * r_{i,t-12,t-2} + v_{i,t}. \tag{4}$$

A positive and significant γ_1 indicates that there is momentum (or short-term continuation) in stock return.

We estimate Equation (4) using Fama-MacBeth (1973). Our hypothesis is that the continuation coefficient is negatively related to the absolute value of the *diff* variable described above. Therefore, we predict that in the following time-series regression:

$$\gamma_{1t} = c_0 + c_1 * |diff|_t + c * X_t + e_t, \tag{5}$$

the coefficient c_1 will be negative, controlling for other factors X that might drive return predictability. The control variables that we include are the state of the market over the previous

[20] We use the median rather than the mean to minimize the influence of outliers.

36 months, momentum gap measured as the difference between the 90th and 10th percentiles of the distribution of cumulative stock returns from month t-12 to t-2, the average and the standard deviation of the distribution of cumulative stock returns from month t-12 to t-2. The market state variable is motivated by Cooper, Gutierrez, and Hameed (2004), who show that relative strength momentum profits depend on the state of the market. The momentum gap variables is motivated by Huang (2015), who shows that relative strength momentum returns are correlated with the ranking period return difference between past relative winners and losers.

Table 9 presents the results from estimating Equation (5). We examine two samples, 1965-2014 and 2000-2014. In the presence of all control variables, the magnitude of the difference between the distribution of recent returns and the historical distribution of returns is significantly negatively related to the return continuation coefficient. This suggests that return predictability based on past returns is strongest when the distribution of recent 11-month returns resembles the historical distribution of 11-month returns. The market state variable of Cooper, Gutierrez, and Hameed (2004) is significant in an univariate regression, but its effect on the continuation coefficient disappears in the presence of the *diff* variable.[21] Overall, the results support our hypothesis that following the historical distribution in classifying winners and losers leads to higher momentum profits.

4 Absolute Strength vs. Time Series Momentum

While relative strength momentum strategies rely on predictability from a security's relative past return, Moskowitz, Ooi, and Pedersen (2012) show that there is also predictability from a security's own past return. They find that for certain equity index, currency, commodity, and bond futures, the recent past excess return (in excess of the T-bill rate) is a positive predictor of the future return. Strategies that go long instruments with positive past excess return and short instruments with negative past excess return produce significantly positive profits. Therefore, the time series momentum strategy documented by Moskowitz, Ooi, and Pedersen (2012) identifies the winners (losers) as the instruments that have gone up (down) in value relative to the T-bill rate.

In this section, we examine a time series momentum strategy similar to the one described in Moskowitz, Ooi, and Pedersen (2012), but we apply it instead to the cross section of U.S. stocks. We can directly compare the profits of this strategy to the ones generated by relative strength and

[21]The results in Table 9 are robust to using the square of *diff* rather than its absolute value.

absolute strength momentum since all of these strategies are applied to individual US stocks. More importantly, our goal is to test whether the time series momentum strategy can explain the profits generated by the absolute strength momentum strategy. Specifically, our objective is to examine whether simply having a positive (negative) excess return over the ranking period is enough to generate momentum in stock returns.

We use common stocks traded on the NYSE, AMEX, and NASDAQ, excluding stocks priced below $1 at the beginning of the holding period. At the beginning of each month t, we compute the cumulative excess returns (in excess of the T-bill rate) of all firms from month t-12 to t-2. We require firms to have at least eight observations of return in the t-12 to t-2 window. Based on their 11-month cumulative excess returns, firms are placed in two value-weighted portfolios. The time series loser portfolio (TSL) consists of stocks with negative 11-month excess returns. The time series winner portfolio (TSW) consists of stocks with positive 11-month excess returns. The portfolios are held over month t, and they are rebalanced monthly. We skip one month between the ranking period for cumulative returns and the start of the portfolio holding period. The time series momentum strategy buys portfolio TSW and sells portfolio TSL.

Table 10 presents several characteristics of portfolios sorted on time series momentum: average return, average excess return, volatility, Fama-French (1993) alpha, CAPM beta, and Sharpe ratio. The table shows that the time series momentum strategy generates significant risk-adjusted profits of 0.46% per month for the period 1965-2014 and insignificant profits for the period 2000-2014. However, the profits of the time series momentum strategy are smaller than the ones documented previously for absolute and relative strength momentum.[22]

Next we test whether time series momentum captures absolute strength momentum. This test is critical since both strategies use securities' own past returns. Table 11 presents results for time-series regressions during the period from 1965 to 2014 in which the dependent variable is the absolute strength momentum strategy and the independent variables are time series momentum or the excess market return, HML and SMB, as well as time series momentum. The absolute strength momentum strategy loads significantly on time series momentum. However, the time-series intercept in both specifications is significantly positive and economically large. Therefore, time series momentum in individual stocks does not explain the returns to the absolute strength

[22] Although the time series momentum strategy that we implement follows a method similar to Moskowitz, Ooi, and Pedersen (2012), our results are not directly comparable to theirs since we use different assets to construct the strategy. We do not scale returns by their ex-ante volatility in constructing the time series momentum strategy in order to keep our method comparable to the one used for absolute and relative strength momentum.

momentum strategy.

Table 11 also presents a specification in which the dependent variable is time series momentum and the independent variables are absolute strength momentum or the market excess return, HML and SMB, as well as absolute strength momentum. The results show that time series momentum is significantly exposed to absolute strength momentum. Once we control for the Fama-French factors, the time-series intercept is not significant and its economic magnitude is negligible. Overall, the results in Table 11 reveal that absolute strength momentum subsumes the information contained in time series momentum but the reverse does not hold. While time series momentum identifies winners and losers based on positive or negative excess returns, absolute strength momentum identifies them based on *significantly* positive or negative returns with respect to the historical benchmark. Results reported previously reveal that the strength of the momentum that stocks experience over the t-12 to t-2 period is key in predicting future momentum continuation.

To understand why stocks with significant movement in either direction have considerably higher momentum compared to stocks with near zero returns (which make up the majority of stocks in the time series momentum portfolios), we investigate the disposition effect explanation of momentum. Grinblatt and Han (2005) provide a theoretical framework in which prospect theory and mental accounting generate the disposition effect, i.e., the higher tendency of investors to sell stocks that have gone up in value since purchase as opposed to stocks that have gone down in value. Investors' decision to buy or sell crucially depends on the purchase price (reference price, RP) of the stock. We hypothesize that a recent significant upward move in the stock price following good news will more likely place the stock in the *capital gain* category for most investors. Disposition-effect-driven sale demand will create a downward price pressure for these stocks, leading to positive momentum in the short run.

Similarly, a recent significant downward move in the stock price following bad news will more likely place the stock in the *capital loss* category for most investors. Investors will be more reluctant to sell these stocks, resulting in a price continuation for the losers. As a result, we expect stocks in the absolute strength decile portfolios to be more prone to disposition-effect-induced trading compared to stocks in the time series momentum portfolios.[23] More specifically, we expect that the time series winner (loser) portfolio will have smaller unrealized capital gains (losses) than the absolute strength winner (loser) portfolio. Therefore, if past "capital gains overhang"

[23]By construction, the decile portfolios of absolute strength momentum include only stocks with significant directional price movements over the portfolio formation period. On the other hand, time series loser and winner portfolios contain many stocks with near zero returns over the previous year.

is not correlated with the return of the stock during the previous year, we conjecture that the spread in capital gains overhang between absolute strength winners and losers will be higher than that between time series winners and losers. To the extent that the disposition effect drives the profitability of momentum, this would result in higher profitability for absolute strength momentum relative to time series momentum.

To test this prediction, we compute the capital gains overhang measure of each stock using the approach described by Frazzini (2006). We then compute the capital gains overhang of the absolute strength and time series winners and losers as the median across the stocks in each portfolio.[24] Untabulated results show that the average capital gains overhang of the absolute strength winners (losers) is 0.17 (-0.75), while that for the time series winners (losers) is 0.09 (-0.15).[25] The difference between the average capital gains overhang of the absolute strength momentum strategy and the time series momentum strategy is 0.69 (t-statistic: 41.36). Furthermore, we identify the stocks that are in the time series winner (loser) portfolio but are not in the absolute strength winner (loser) portfolio. Their average capital gains overhang has an even smaller magnitude at 0.07 for the winners (vs. 0.17 for absolute strength winners) and -0.10 for the losers (vs. -0.75 for absolute strength losers).[26] Overall, these results suggest that classifying stocks into time series winners or losers does not identify stocks with large unrealized capital gains or losses. To the extent that the capital gains overhang effect drives the profitability of momentum, these results provide a potential explanation for the low profitability of the time series momentum strategy.

5 Robustness

This section examines several additional aspects of the data. The goal is to determine whether our previous results are robust to slight variations in the empirical analysis. All new results from this section are tabulated in Appendix A.

[24]We use the median to mitigate the effect of outliers.

[25]These numbers are based on computing capital gains overhang as $(P_t - RP_t)/P_t$, where P_t is the current price of the stock and RP_t is the reference price which measures the stock's cost basis. We also use a return-based measure of capital gains overhang, $(P_t - RP_t)/RP_t$, and get similar results: the average capital gains overhang of the absolute strength winners (losers) is 0.23 (-0.40), while that for the time series winners (losers) is 0.10 (-0.12).

[26]We obtain similar differences when we use the fraction of stocks with capital gains or losses. For example, 31% of stocks that are in the time series loser portfolio but not in the absolute strength loser portfolio have capital gains. The percentage of stocks with capital gains is much lower in the absolute strength loser portfolio (9.7%). The difference is less striking for the percentage of stocks with capital losses in the winner portfolios (33% for time series winners and 27% for absolute strength winners). We obtain a bigger difference when we condition on the months in which absolute strength momentum does not trade. For example, during these months, for 41% of stocks in the time series winner portfolio investors are actually sitting on capital losses.

5.1 Overlapping Absolute Strength Return Breakpoints

To classify stocks into absolute strength winners or losers, we use the historical distribution of past returns with non-overlapping observations. In order to examine whether our main results are driven by using non-overlapping historical return observations, we repeat the analysis using overlapping observations. Specifically, at the beginning of each month t, we compute the cumulative returns of all stocks over the period t-12 to t-2. To determine whether these cumulative returns are high or low, we look at the distribution of all previous 11-month cumulative returns across stocks and across time. For example, at the beginning of month t, we record cumulative returns for all stocks over the period t-12 to t-2, t-13 to t-3, t-14 to t-4, etc. These overlapping 11-month return observations represent the historical distribution of cumulative returns. If a stock's cumulative return over t-12 to t-2 falls in the top (bottom) 10% of the historical distribution, we classify that stock as an absolute strength winner (loser). We repeat this process every month. Therefore, the historical distribution of 11-month cumulative returns is updated continuously.

Figure A1 plots the absolute strength winner and loser cumulative return breakpoints based on the method described above, from January 1965 to December 2014. We use return data back to 1927 to determine performance breakpoints. At the beginning of the sample, the 11-month absolute strength winner cutoff starts approximately at a 58% return, and by the end of the sample, it is updated up to an approximate 67% return. The absolute strength loser cutoff starts with an approximate -34% return and is updated down to an approximate -48% return by the end of the sample period. As in the case of non-overlapping breakpoints, the definition of an absolute strength winner or loser is remarkably stable over time.

We form ten absolute strength momentum portfolios based on these overlapping historical return breakpoints. Table A1 presents monthly characteristics for these portfolios. The results in the table are similar to results reported using non-overlapping return breakpoints.

5.2 NYSE Breakpoints

The absolute strength momentum strategy that we examine uses the whole cross section of CRSP common stocks to define our cumulative return breakpoints. In order to alleviate the concern that the CRSP breakpoints are biased due to the presence of many small NASDAQ and AMEX stocks, we also use NYSE breakpoints.

We replicate Tables 1 and 2 using NYSE breakpoints. In particular, for relative strength momentum, cumulative return breakpoints are constructed based solely on NYSE firms. These breakpoints are applied to all NYSE, AMEX, and NASDAQ stocks to construct ten relative strength momentum portfolios. Similarly, for absolute strength momentum, cumulative return breakpoints are constructed based on the historical distribution of NYSE firms only. These breakpoints are applied to all NYSE, AMEX, and NASDAQ stocks to construct ten absolute strength momentum portfolios. We still impose the restriction that the absolute loser and winner portfolios consist of at least 30 stocks.

Results for using NYSE breakpoints are presented in Tables A2 (absolute strength momentum) and A3 (relative strength momentum). The results show that in both sample periods, absolute strength momentum has higher profits and a higher Sharpe ratio than relative strength momentum. The magnitude of absolute strength momentum profits is smaller than that reported in Table 1. The reason behind this is in the definition of absolute strength winners and losers according to the historical breakpoints based on NYSE firms. The absolute strength winner (loser) breakpoint based on NYSE firms is lower in magnitude than the absolute strength winner (loser) breakpoint based on the whole cross section of firms. Since absolute strength momentum profits increase monotonically with the magnitude of winner/loser breakpoints, the NYSE breakpoints produce lower momentum profits. Overall, the results are robust to using only NYSE firms in deriving historical absolute strength breakpoints.

5.3 Starting the Analysis in 1978

The historical distribution of returns used to define absolute strength breakpoints uses the whole cross section of CRSP common stocks. However, the cross section of stocks contains only NYSE firms until June of 1962, and only NYSE and AMEX stocks until about December 1972. To facilitate the comparison across time between the historical distribution of returns and the most recent distribution of returns, we repeat the empirical analysis in the main part of the paper starting in January 1978. This is five years after the introduction of NASDAQ firms in the CRSP sample. We wait five years in order to accumulate some historical information for the period during which all three exchanges (NYSE, AMEX, and NASDAQ) were operational at the same time. Therefore, we begin our analysis at a point in time where NYSE, AMEX, and NASDAQ firms are trading in the market.

Panel A of Table A4 presents sample statistics for ten portfolios sorted on absolute strength momentum for the period 1978 to 2014. Portfolios 1 through 10 correspond to absolute strength performance breakpoints based on the historical distribution of returns, starting in 1978. The statistics are computed over the months during which both portfolios 1 and 10 consist of at least 30 stocks. The strategy that buys absolute strength winners and sells absolute strength losers is presented in the last column. The table shows that the absolute strength momentum strategy generates significant profits of 2.20% per month. The risk-adjusted return of the strategy is 2.51% per month. The Share ratio of absolute strength momentum is 0.30.

Panel B of Table A4 presents the monthly statistics for ten portfolios sorted on relative strength momentum from 1978 to 2014. The table shows that the relative strength momentum strategy is also profitable from 1978 to 2014. However, its performance is worse than the performance of absolute strength momentum for the same period. Furthermore, the Sharpe ratio of relative strength momentum is smaller than the Sharpe ratio of absolute strength momentum.

Table A5 examines the performance of absolute and relative strength momentum in different states for the period 1978-2014. Similar to previous results, relative strength momentum severely underperforms absolute strength momentum at times when the absolute strength loser or winner portfolios are not well-diversified. For example, relative strength momentum has an average return of -3.43% per month when there are fewer than 30 absolute strength losers in the market, and an average return of -7.94% per month when there are fewer than 30 absolute strength winners in the market. At times when the absolute strength momentum portfolios are well-diversified, relative strength momentum still underperforms absolute strength momentum (1.94% vs 2.25%, respectively).

5.4 Different Ranking and Holding Periods

In this section we examine the profitability of traditional momentum strategies as in Jegadeesh and Titman (1993) over the sample periods 1965-2014 and 2000-2014. These strategies select stocks based on their performance over the past 3, 6, 9, or 12 (J) months and hold them for either 3, 6, 9, or 12 (K) months. Namely, at the beginning of each month t, we calculate the cumulative return of each stock over the past J months. To calculate the breakpoints for classifying stocks into relative strength winners and losers in month t, we record every tenth percentile of the resulting cumulative return distribution. Relative strength winners are stocks with prior cumulative return above the 90th percentile, while relative strength losers are stocks with prior cumulative return below the 10th percentile. The relative strength winner and loser breakpoints are re-calculated every month following the same method. After the cumulative return breakpoints are identified, we sort stocks into 10 equally-weighted portfolios based on their cumulative returns in the past J months. We hold these portfolios for K months (t+1 to t+K). As a result, we have K overlapping portfolios where each one is assigned an equal weight in the portfolio. We construct a relative strength momentum strategy that buys the relative strength winner portfolio (top past return decile) and sells the relative strength loser portfolio (bottom past return decile). We compute portfolio returns using monthly CRSP stock data and exclude stocks priced below $1 at the beginning of the holding period.

Table A6 presents summary statistics for four momentum strategies, where J=K=3,6,9,12. The table also presents the statistics for the relative strength loser and winner portfolio of each strategy. The results show that the relative strength momentum strategies of Jegadeesh and Titman (1993) produce significant profits over the full sample period 1965-2014, but their profits are much smaller and insignificant over the recent period 2000-2014.

In Table A7, we examine the performance of the same Jegadeesh and Titman (1993) type strategies, but we use absolute strength benchmarks to classify stocks into absolute strength winners and losers. The results show that absolute strength momentum still has much higher profits than relative strength momentum, both in raw and risk-adjusted returns.

Untabulated results show that when we skip a week between portfolio ranking and holding period, the profits to both relative strength and absolute strength momentum improve slightly. This is consistent with results reported in Jegadeesh and Titman (1993).

5.5 Not Skipping a Month between Ranking Period and Holding Period

Finally, we examine a strategy that selects stocks based on their performance over t-12 to t-1 and holds them over month t. This is a strategy that does not skip a month between portfolio ranking period and the holding period for returns. We examine both the relative strength and absolute strength version of this strategy. Results are reported in Table A8. The table shows that absolute strength momentum still produces significant profits over the periods from 1965 to 2014 and 2000 to 2014. Relative strength momentum is not profitable in the period 2000 to 2014.

6 Conclusion

Motivated by theoretical models of how momentum arises in stock returns and the important role absolute price changes play in investor decision making, we examine the magnitude and the direction of securities' own past returns. We document a new pattern in stock returns: large (small) positive returns over the recent past continue to be large (small) and positive in the near future. Similarly, large (small) negative returns over the recent past continue to be large (small) and negative in the near future. An investment strategy designed to profit from return momentum buys stocks with *significantly positive* recent returns and shorts stocks with *significantly negative* recent returns. This new strategy that we call absolute strength momentum generates a risk-adjusted return of 2.42% per month with a monthly Sharpe ratio of 0.32 from 1965 to 2014. It also performs well over the 2000-2014 period, which includes the recent Great Recession: its risk-adjusted return is 1.51% per month with a monthly Sharpe ratio of 0.18.

Absolute strength momentum is related to but different from relative strength momentum examined by Jegadeesh and Titman (1993). A stock with positive momentum under the relative strength strategy does not necessarily have positive momentum under the absolute strength strategy. The relative strength strategy does not guarantee winner (loser) portfolios to have positive (negative) sorting period cumulative returns. For example, when the sorting window overlaps with recessionary periods and/or significant market declines, the 90% cross-sectional return cutoff to define winners can be negative. As a result, the relative winner portfolio will include many stocks that declined in value over the sorting period.

We show that absolute strength momentum not only does well over various sample periods, but also has several other features that distinguish it from relative strength momentum. A recent study by Novy-Marx (2012) suggests that an asset's relative performance over the first half of the preceding year seems to better predict returns compared to its relative performance over the most recent past. For example, Novy-Marx finds that stocks that are relative winners over the past six months but relative losers over the first half of the preceding year, tend to significantly underperform stocks that are relative losers over the past six months but relative winners over the first half of the preceding year. This evidence implies that there is an "echo" in returns rather than "momentum." The absolute strength momentum strategy, however, is robust to the "echo" effect in returns documented by Novy-Marx. We show that absolute performance over the first half of the preceding year and absolute performance over the most recent past are equally important in predicting future performance.

Furthermore, there are times when the relative strength momentum strategy experiences severe crashes that can significantly reduce the accumulated gains from the strategy (e.g., Daniel and

Moskowitz (2014)). For example, in August 1932, a strategy that buys the previous 11-month relative winners and sells the previous 11-month relative losers returned a negative 78%. More recently, in April 2009, the same strategy returned a negative 46%. The absolute strength momentum strategy we examine is not subject to such severe crashes. More importantly, we show that we are able to avoid momentum crash periods in real time by following absolute strength momentum rules.

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Figure 1. **Cumulative Return Breakpoints for Absolute Strength Momentum**

This figure reports the cumulative return breakpoints for absolute winners and absolute losers. The absolute winner and loser breakpoints are based on the historical distribution of 11-month cumulative returns. The cutoffs are determined by the top 10% of that distribution for the winners and the bottom 10% of the distribution for the losers.

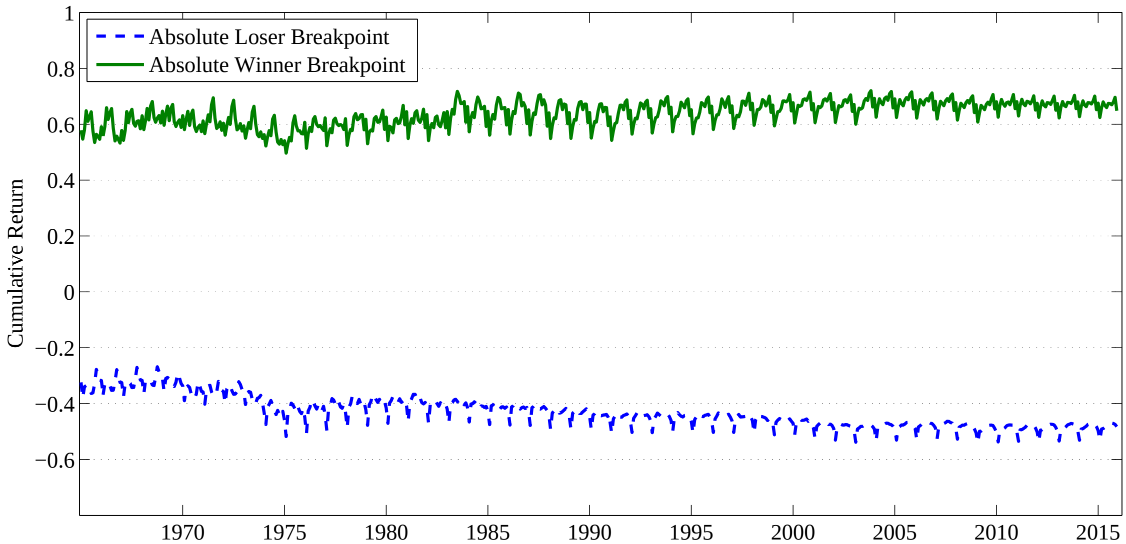


Figure 2. **Cumulative Return Breakpoints for Relative Strength Momentum**

This figure reports the cumulative return breakpoints for relative winners and relative losers. The relative winner and loser breakpoints are based on the distribution of the most recent 11-month cumulative returns. The cutoffs are determined by the top 10% of the distribution for the winners and the bottom 10% of the distribution for the losers. On the same graph we plot the cumulative return breakpoints for absolute winners and absolute losers from Figure 1.

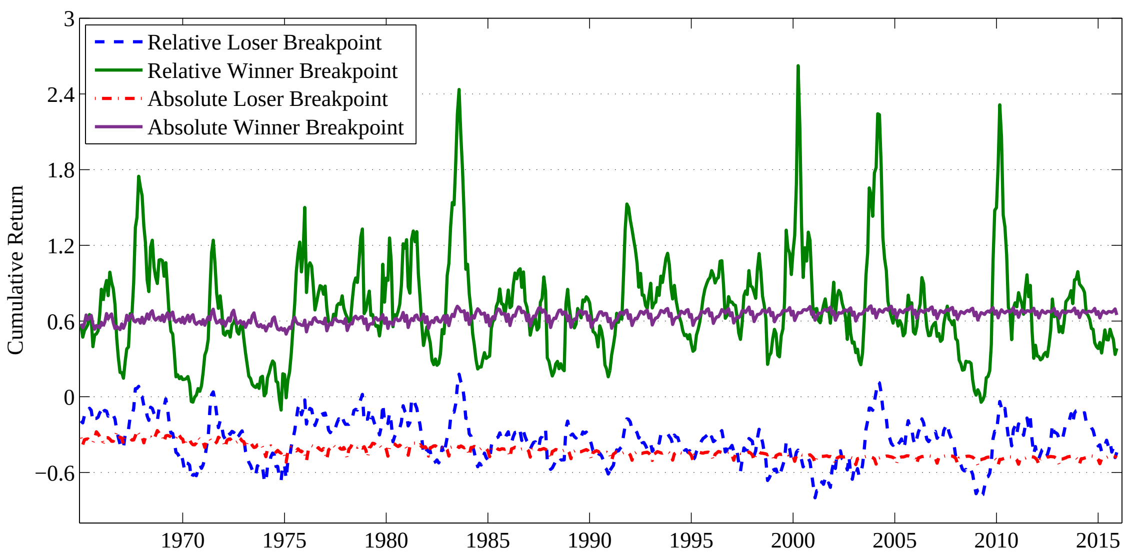


Figure 3. **Number of Firms in Absolute Strength Loser/Winner Portfolio**

This figure reports the number of firms over time in the winner and loser portfolio of the absolute strength momentum strategy. Absolute winners and losers are identified based on the historical distribution of 11-month cumulative returns.

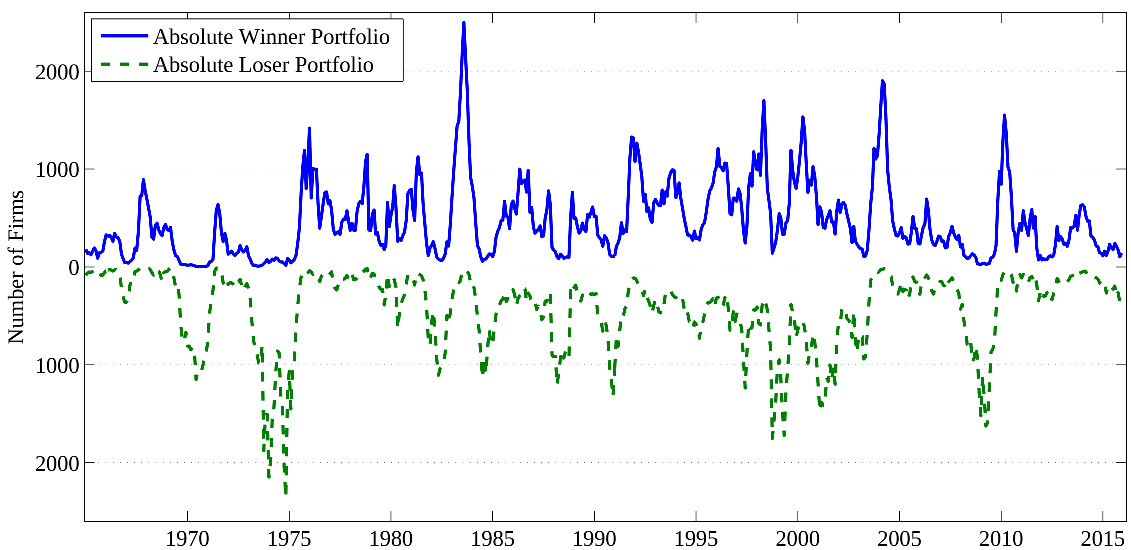
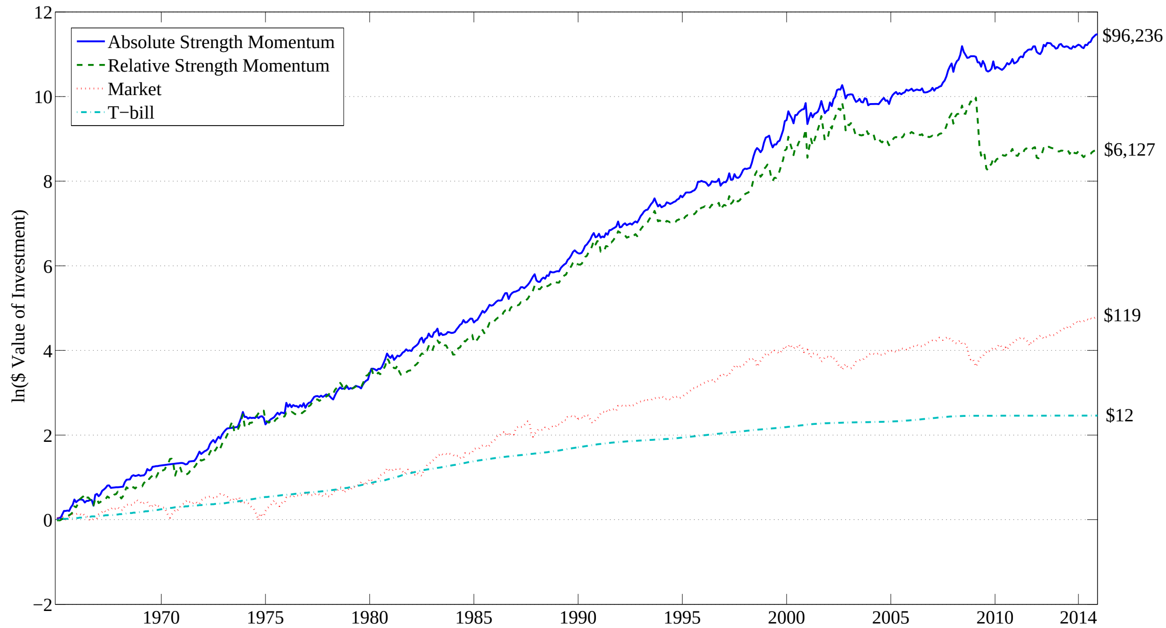


Figure 4. **Cumulative Gains from Investment**

This figure reports the cumulative gains from investing $1 in relative strength momentum, absolute strength momentum, the market, and the one-month T-bill over 1965-2014 (Panel A) and 2000-2014 (Panel B).

A: 1965-2014



B: 2000-2014

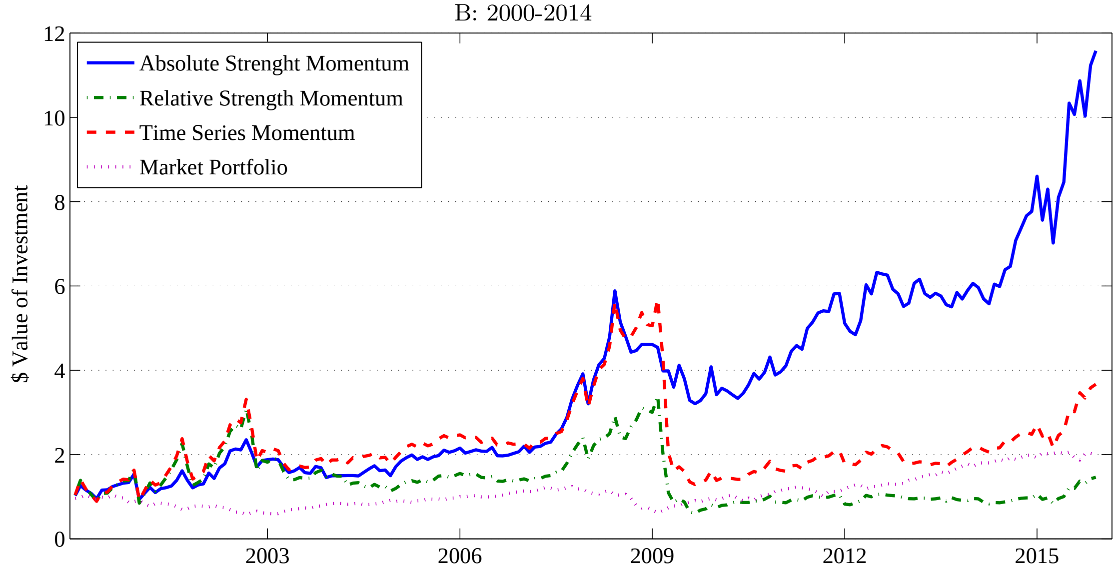


Table 1. **Absolute Strength Portfolio Characteristics: Well-diversified Portfolios**

This table presents monthly characteristics of absolute strength portfolios over two sample periods. The average return, volatility, and alpha are in percent. The alpha and beta are estimated from a full-period time-series regression of each portfolio's excess return on the excess return of the CRSP value-weighted index, HML, and SMB. The absolute strength portfolios are constructed using common stocks on the NYSE, AMEX and NASDAQ, excluding stocks priced below $1 at the beginning of the holding period. At the beginning of each month t, stocks are sorted into value-weighted portfolios based on their cumulative returns over t-12 to t-2 and held for one month. The cumulative return breakpoints are determined based on the historical distribution of non-overlapping 11-month returns since 1927. The strategy that buys absolute winners and sells absolute losers is presented in the last column. Panels A and B correspond to sample periods 1965-2014 and 2000-2014, respectively.

Panel A: 1965-2014											
Absolute Strength Decile Portfolios											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\bar{R}$	-0.38	0.33	0.42	0.69	0.70	0.93	0.97	1.17	1.39	1.74	2.16
$t(\bar{R})$	-1.15	1.28	1.99	4.02	4.22	5.71	6.06	6.75	6.35	6.31	7.82
$\bar{R}$-$\bar{R}_f$	-0.79	-0.08	0.01	0.28	0.29	0.52	0.56	0.76	0.98	1.33	2.16
σ	8.16	6.27	5.15	4.23	4.08	4.01	3.95	4.25	5.38	6.76	6.77
α	-1.50	-0.71	-0.49	-0.13	-0.10	0.12	0.21	0.38	0.54	0.88	2.42
$t(\alpha)$	-6.75	-4.48	-4.80	-1.37	-1.15	1.57	2.65	4.20	4.26	5.43	8.71
β	1.23	1.10	0.95	0.82	0.83	0.83	0.79	0.83	0.96	1.01	-0.22
SR	-0.10	-0.01	0.00	0.07	0.07	0.13	0.14	0.18	0.18	0.20	0.32
Cumulative Return (t-12, t-2) Breakpoints											
	10%	20%	30%	40%	50%	60%	70%	80%	90%		
Average	-42.91	-26.40	-14.88	-5.55	2.93	11.88	22.32	36.74	63.69		
Min	-53.95	-35.78	-23.21	-12.54	-3.41	5.32	15.09	27.75	49.67		
Max	-26.80	-14.29	-5.47	2.19	9.49	17.46	27.33	42.04	72.03		
SD	5.51	4.34	3.40	2.66	2.19	1.91	1.88	2.44	4.55		

Panel B: 2000-2014											
Absolute Strength Decile Portfolios											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\bar{R}$	-0.81	0.04	0.21	0.46	0.26	0.57	0.53	0.64	0.53	0.69	1.51
$t(\bar{R})$	-1.10	0.08	0.48	1.40	0.80	2.04	2.03	2.10	1.28	1.32	2.41
$\bar{R}$-$\bar{R}_f$	-0.97	-0.11	0.06	0.31	0.11	0.42	0.38	0.49	0.38	0.54	1.51
σ	9.91	7.35	5.94	4.41	4.37	3.79	3.54	4.12	5.59	7.08	8.39
α	-1.43	-0.53	-0.28	0.06	-0.11	0.19	0.21	0.26	-0.01	0.12	1.55
$t(\alpha)$	-3.17	-1.74	-1.13	0.32	-0.76	1.47	1.54	1.53	-0.03	0.37	2.57
β	1.70	1.38	1.13	0.86	0.90	0.78	0.69	0.79	0.96	1.04	-0.66
SR	-0.10	-0.02	0.01	0.07	0.02	0.11	0.11	0.12	0.07	0.08	0.18
Cumulative Return (t-12, t-2) Breakpoints											
	10%	20%	30%	40%	50%	60%	70%	80%	90%		
Average	-48.32	-30.24	-17.60	-7.41	1.75	11.34	22.50	37.97	67.19		
Min	-53.95	-35.42	-21.94	-11.01	-1.60	7.90	18.77	33.38	60.01		
Max	-45.43	-28.08	-15.27	-4.95	4.35	14.19	25.58	41.53	72.03		
SD	1.74	1.57	1.34	1.18	1.15	1.20	1.29	1.57	2.40		

Table 2. **Relative Strength Portfolio Characteristics**

This table presents monthly characteristics of relative strength portfolios over two sample periods. The average return, volatility, and alpha are in percent. The alpha and beta are estimated from a full-period time-series regression of each portfolio's excess return on the excess return of the CRSP value-weighted index, HML, and SMB. The relative strength portfolios are constructed using common stocks on the NYSE, AMEX and NASDAQ, excluding stocks priced below $1 at the beginning of the holding period. At the beginning of each month t, stocks are sorted into 10 value-weighted portfolios based on their cumulative returns over t-12 to t-2 and held for one month. The strategy that buys relative winners and sells relative losers is presented in the last column. Panels A and B correspond to sample periods 1965-2014 and 2000-2014, respectively.

Panel A: 1965-2014											
Relative Strength Decile Portfolios											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\bar{R}$	-0.25	0.34	0.48	0.79	0.84	0.82	0.98	1.12	1.20	1.60	1.85
$t(\bar{R})$	-0.65	1.09	1.89	3.64	4.23	4.41	5.32	5.82	5.65	5.72	5.38
$\bar{R}$-$\bar{R}_f$	-0.67	-0.08	0.07	0.38	0.43	0.41	0.57	0.71	0.79	1.19	1.85
σ	9.61	7.57	6.29	5.34	4.89	4.58	4.54	4.72	5.23	6.84	8.43
α	-1.59	-0.87	-0.62	-0.23	-0.13	-0.12	0.07	0.21	0.29	0.68	2.27
$t(\alpha)$	-6.43	-4.77	-6.31	-2.13	-1.54	-1.82	1.06	2.82	3.01	4.71	6.66
β	1.50	1.33	1.18	1.07	1.02	0.99	0.97	0.98	0.98	1.03	-0.46
SR	-0.07	-0.01	0.01	0.07	0.09	0.09	0.13	0.15	0.15	0.17	0.22
Cumulative Return (t-12, t-2) Breakpoints											
	10%	20%	30%	40%	50%	60%	70%	80%	90%		
Average	-39.15	-23.35	-12.12	-2.73	6.00	15.21	26.08	41.20	69.86		
Min	-86.68	-76.24	-67.84	-59.53	-51.20	-43.12	-33.33	-22.76	-10.01		
Max	9.87	31.03	47.83	64.12	81.06	98.94	123.09	161.69	250.00		
SD	19.63	19.30	18.82	18.72	19.22	20.51	22.90	27.69	40.06		
Panel B: 2000-2014											
Relative Strength Decile Portfolios											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\bar{R}$	0.01	0.25	0.37	0.58	0.60	0.56	0.72	0.63	0.46	0.76	0.75
$t(\bar{R})$	0.01	0.34	0.66	1.28	1.49	1.72	2.42	1.93	1.29	1.44	0.87
$\bar{R}$-$\bar{R}_f$	-0.14	0.10	0.22	0.43	0.44	0.41	0.56	0.47	0.31	0.61	0.75
σ	12.64	9.70	7.56	6.12	5.39	4.40	4.00	4.38	4.84	7.10	11.51
α	-0.73	-0.44	-0.25	0.01	0.06	0.06	0.20	0.12	-0.06	0.13	0.86
$t(\alpha)$	-1.25	-1.05	-0.80	0.07	0.35	0.46	1.72	0.83	-0.32	0.45	1.11
β	2.18	1.78	1.43	1.23	1.10	0.92	0.82	0.88	0.84	0.95	-1.24
SR	-0.01	0.01	0.03	0.07	0.08	0.09	0.14	0.11	0.06	0.09	0.06
Cumulative Return (t-12, t-2) Breakpoints											
	10%	20%	30%	40%	50%	60%	70%	80%	90%		
Average	-43.81	-26.52	-14.56	-4.75	4.23	13.68	24.91	40.90	72.86		
Min	-86.68	-76.24	-67.84	-59.53	-51.20	-43.12	-33.33	-22.76	-5.40		
Max	9.87	23.99	34.18	44.88	56.55	72.17	95.23	136.57	250.00		
SD	21.85	22.12	20.92	19.77	19.38	20.04	22.21	27.98	46.02		

Table 3. **Absolute Strength Momentum vs. Relative Strength Momentum**

This table reports time-series regressions from 1965 to 2014. Portfolio AbsMom corresponds to a strategy that buys absolute winners and sells absolute losers. Portfolio RelMom corresponds to the strategy that buys relative winners and sells relative losers. The other variables are the excess market return (MKT) and the value and size factors HML and SMB of Fama and French (1993). The adjusted R^2 of each regression is reported in the last column.

	Independent Variables						
Dependent Variable	Intercept	MKT-RF	HML	SMB	RelMom	AbsMom	Adj. R^2
AbsMom	0.0092				0.69		0.64
	(5.14)				(32.93)		
AbsMom	0.0100	0.07	-0.08	-0.03	0.63		0.60
	(5.42)	(1.63)	(-1.23)	(-0.56)	(29.23)		
RelMom	-0.0021					0.94	0.64
	(-0.97)					(32.93)	
RelMom	-0.0001	-0.26	-0.11	-0.01		0.94	0.62
	(-0.04)	(-4.94)	(-1.40)	(-0.17)		(29.23)	

Table 4. **Is Relative Strength Momentum Really Momentum?**

This table reports the average monthly returns (and corresponding t-statistics) of portfolios double-sorted on intermediate (IR) and recent returns (RR). Intermediate returns are measured from 12 to seven months prior to portfolio formation. Recent returns are measured from six to two months prior to portfolio formation. Return breakpoints are computed using relative strength. Portfolio IR1 corresponds to relative losers over months t-12 to t-7, while portfolio IR5 corresponds to relative winners over months t-12 to t-7. Portfolio RR1 corresponds to relative losers over months t-6 to t-2, while portfolio RR5 corresponds to relative winners over months t-6 to t-2. Portfolio returns are value-weighted. Return spreads for each IR and RR group are also reported. Panels A and B correspond to sample periods 1965-2014 and 2000-2014, respectively.

Panel A: 1965-2014						
	IR1	IR2	IR3	IR4	IR5	IR5-IR1
RR1	-0.31	0.16	0.61	0.38	0.93	1.24
	(-0.79)	(0.44)	(1.98)	(1.24)	(2.89)	(4.85)
RR2	0.40	0.84	0.92	0.89	1.39	0.99
	(1.29)	(3.28)	(3.94)	(3.98)	(5.13)	(4.33)
RR3	0.20	0.76	0.85	1.15	1.31	1.11
	(0.70)	(3.50)	(4.39)	(5.96)	(5.41)	(4.44)
RR4	0.41	0.71	0.86	1.10	1.47	1.06
	(1.62)	(3.49)	(4.46)	(5.61)	(6.13)	(4.87)
RR5	0.33	0.72	1.11	1.11	1.67	1.34
	(1.16)	(3.15)	(5.07)	(4.84)	(5.88)	(5.93)
RR5-RR1	0.64	0.56	0.50	0.73	0.73	
	(2.15)	(1.95)	(1.97)	(2.73)	(2.79)	

Panel B: 2000-2014						
	IR1	IR2	IR3	IR4	IR5	IR5-IR1
RR1	-0.33	-0.05	0.28	0.20	0.60	0.93
	(-0.36)	(-0.06)	(0.41)	(0.29)	(0.90)	(1.59)
RR2	0.42	0.96	0.61	0.55	0.99	0.56
	(0.62)	(1.71)	(1.23)	(1.25)	(1.88)	(1.15)
RR3	0.10	0.59	0.56	0.81	0.74	0.64
	(0.16)	(1.34)	(1.42)	(2.54)	(1.63)	(1.17)
RR4	0.52	0.49	0.64	0.63	0.60	0.07
	(1.05)	(1.27)	(1.95)	(1.90)	(1.40)	(0.15)
RR5	0.01	0.58	0.43	0.61	0.68	0.67
	(0.02)	(1.35)	(1.05)	(1.58)	(1.28)	(1.32)
RR5-RR1	0.34	0.63	0.15	0.40	0.08	
	(0.48)	(0.83)	(0.24)	(0.62)	(0.12)	

Table 5. **11-month Absolute and Relative Strength Ranks of Intermediate Return/Recent Return Portfolios**

This table reports the average 11-month absolute strength and relative strength ranks (and corresponding standard deviations) of portfolios double-sorted on intermediate (IR) and recent returns (RR). Intermediate returns are measured from 12 to seven months prior to portfolio formation. Recent returns are measured from six to two months prior to portfolio formation. Return breakpoints for IR and RR are computed using relative strength. Portfolio IR1 corresponds to relative losers over months t-12 to t-7, while portfolio IR5 corresponds to relative winners over months t-12 to t-7. Portfolio RR1 corresponds to relative losers over months t-6 to t-2, while portfolio RR5 corresponds to relative winners over months t-6 to t-2. Two sample periods, 1965-2014 and 2000-2014, are examined.

	Absolute Ranks						Relative Ranks				
	Panel A: 1965-2014						Panel C: 1965-2014				
	IR1	IR2	IR3	IR4	IR5		IR1	IR2	IR3	IR4	IR5
RR1	1.30	2.00	2.76	3.68	5.87	RR1	1.13	1.77	2.44	3.34	5.92
	(0.61)	(1.10)	(1.51)	(1.89)	(2.66)		(0.34)	(0.58)	(0.79)	(1.15)	(2.32)
RR2	1.97	3.21	4.30	5.45	7.35	RR2	1.72	2.97	4.12	5.53	7.88
	(1.07)	(1.47)	(1.69)	(1.85)	(2.08)		(0.57)	(0.59)	(0.65)	(0.82)	(1.26)
RR3	2.62	4.20	5.37	6.55	8.16	RR3	2.28	4.01	5.46	6.93	8.75
	(1.41)	(1.66)	(1.77)	(1.82)	(1.76)		(0.76)	(0.66)	(0.63)	(0.68)	(0.82)
RR4	3.33	5.22	6.45	7.55	8.89	RR4	2.98	5.25	6.81	8.08	9.38
	(1.74)	(1.83)	(1.81)	(1.71)	(1.41)		(1.08)	(0.81)	(0.67)	(0.61)	(0.56)
RR5	5.03	7.07	8.05	8.84	9.69	RR5	5.06	7.52	8.59	9.33	9.93
	(2.67)	(2.10)	(1.76)	(1.43)	(0.79)		(2.34)	(1.33)	(0.85)	(0.57)	(0.25)
	Panel B: 2000-2014						Panel D: 2000-2014				
	IR1	IR2	IR3	IR4	IR5		IR1	IR2	IR3	IR4	IR5
RR1	1.41	2.16	2.96	3.84	5.92	RR1	1.14	1.79	2.45	3.33	5.91
	(0.73)	(1.25)	(1.67)	(2.03)	(2.72)		(0.34)	(0.59)	(0.81)	(1.21)	(2.42)
RR2	2.13	3.40	4.44	5.51	7.38	RR2	1.74	2.99	4.14	5.57	7.92
	(1.25)	(1.64)	(1.77)	(1.84)	(2.02)		(0.58)	(0.59)	(0.67)	(0.87)	(1.30)
RR3	2.82	4.33	5.42	6.60	8.21	RR3	2.27	4.01	5.49	6.98	8.79
	(1.57)	(1.73)	(1.70)	(1.66)	(1.65)		(0.77)	(0.68)	(0.64)	(0.69)	(0.82)
RR4	3.47	5.26	6.45	7.63	8.99	RR4	2.94	5.24	6.83	8.11	9.40
	(1.83)	(1.81)	(1.65)	(1.52)	(1.24)		(1.12)	(0.86)	(0.68)	(0.61)	(0.55)
RR5	4.93	7.01	8.08	8.92	9.75	RR5	4.86	7.47	8.59	9.33	9.93
	(2.71)	(2.05)	(1.57)	(1.22)	(0.62)		(2.42)	(1.39)	(0.86)	(0.57)	(0.25)

Table 6. **Is Absolute Strength Momentum Really Momentum?**

This table reports the average monthly returns (and corresponding t-statistics) of portfolios double-sorted on intermediate (IR) and recent returns (ARR). Intermediate returns are measured from 12 to seven months prior to portfolio formation. Recent returns are measured from six to two months prior to portfolio formation. Intermediate return breakpoints are computed based on absolute strength. Portfolio IR1 corresponds to absolute losers over months t-12 to t-7, while portfolio IR5 corresponds to absolute winners over months t-12 to t-7. Recent return breakpoints are computed based on absolute strength. Portfolio RR1 corresponds to absolute losers over months t-6 to t-2, while portfolio RR5 corresponds to absolute winners over months t-6 to t-2. Portfolio returns are value-weighted. Return spreads for each IR and RR group are also reported. Panels A and B correspond to sample periods 1965-2014 and 2000-2014, respectively.

Panel A: 1965-2014						
	IR1	IR2	IR3	IR4	IR5	IR5-IR1
RR1	-0.31	0.24	0.17	0.10	0.67	0.98
	(-0.95)	(0.87)	(0.69)	(0.38)	(2.38)	(4.42)
RR2	0.08	0.54	0.56	0.66	1.02	0.97
	(0.29)	(2.70)	(3.16)	(3.77)	(4.55)	(4.99)
RR3	0.01	0.56	0.66	0.78	0.95	1.01
	(0.05)	(3.24)	(4.53)	(4.96)	(4.55)	(5.60)
RR4	0.19	0.31	0.73	0.85	0.92	0.99
	(0.78)	(1.76)	(4.85)	(5.38)	(4.33)	(5.66)
RR5	0.53	0.73	1.00	1.05	1.41	1.02
	(1.96)	(3.57)	(5.38)	(5.13)	(5.40)	(5.77)
RR5-RR1	1.03	0.62	1.16	1.03	0.82	
	(4.29)	(2.89)	(5.42)	(5.02)	(3.73)	
Panel B: 2000-2014						
	IR1	IR2	IR3	IR4	IR5	IR5-IR1
RR1	-0.48	-0.23	0.24	-0.31	0.64	1.04
	(-0.64)	(-0.38)	(0.42)	(-0.56)	(1.09)	(2.21)
RR2	-0.02	0.61	0.46	0.35	0.31	0.18
	(-0.03)	(1.43)	(1.26)	(0.98)	(0.68)	(0.42)
RR3	-0.77	0.30	0.45	0.42	0.36	0.89
	(-1.59)	(0.90)	(1.45)	(1.42)	(0.84)	(2.20)
RR4	-0.24	0.10	0.65	0.48	0.26	0.41
	(-0.51)	(0.31)	(2.57)	(1.59)	(0.60)	(1.07)
RR5	0.72	0.38	0.85	0.81	0.60	-0.03
	(1.23)	(0.92)	(2.25)	(1.98)	(1.13)	(-0.07)
RR5-RR1	1.56	0.83	0.74	1.10	-0.09	
	(2.84)	(1.67)	(1.46)	(2.36)	(-0.19)	

Table 7. **Worst Monthly Momentum Returns**

This table presents the 15 worst monthly returns to the relative strength momentum strategy (Panel A) and the absolute strength momentum strategy (Panel B) from 1927 to 2014. Panel A (B) also shows the returns of the absolute (relative) strength momentum strategy in the worst months of the relative (absolute) strength strategy. The number of firms in the loser and winner portfolio of each strategy is shown. The one-year lagged market return (t-12,t-1) and the contemporaneous market return (t) are also presented.

Panel A	Relative Momentum			Absolute Momentum			Market Return	
Date	P10-P1	P1 firms	P10 firms	P10-P1	P1 firms	P10 firms	t-12,t-1	t
1932-08	-77.67	53	64	0.03	236	4	-51.05	37.09
1932-07	-59.66	46	65	0.03	225	2	-65.84	33.87
2001-01	-48.71	312	590	-39.02	1194	432	-11.71	3.67
2009-04	-45.71	185	409	0.01	1625	27	-37.00	10.20
1933-04	-44.20	49	57	0.10	22	42	-12.47	38.95
1939-09	-41.12	54	73	0.01	5	25	-1.03	16.89
2009-03	-40.45	141	412	-12.27	1334	39	-42.63	8.97
2002-11	-35.60	275	502	-16.62	746	263	-13.62	6.08
1938-06	-33.94	62	75	0.00	181	0	-39.18	23.87
1931-06	-29.45	58	69	0.08	201	3	-45.51	13.98
2009-08	-27.41	259	397	-13.44	842	99	-18.91	3.34
1933-05	-26.96	59	61	0.04	15	131	48.04	21.47
2001-11	-26.30	312	557	-12.91	1198	335	-26.16	7.71
2001-10	-24.19	277	564	-14.04	1023	459	-29.67	2.68
1970-09	-23.88	214	215	0.54	1073	6	-14.68	4.72
Panel B	**Absolute Momentum**			**Relative Momentum**			**Market Return**	
Date	P10-P1	P1 firms	P10 firms	P10-P1	P1 firms	P10 firms	t-12,t-1	t
2001-01	-39.02	1194	432	-48.71	312	590	-11.70	3.67
2008-01	-18.15	431	203	-21.35	327	429	5.68	-6.15
2002-11	-16.62	746	263	-35.60	275	502	-13.60	6.08
2010-01	-16.25	136	845	-8.19	319	367	28.36	-3.36
1999-04	-16.01	1488	333	-18.43	550	650	13.64	4.7
1996-11	-15.18	457	702	-14.64	524	650	21.87	6.66
1983-05	-15.08	163	1489	-6.33	281	454	51.02	1.21
1927-11	-14.54	31	89	-7.99	49	52	.	6.79
1997-05	-14.53	955	369	-16.58	534	677	17.46	7.23
1975-01	-14.21	1065	68	-21.22	369	446	-27.70	14.24
2001-10	-14.04	1023	459	-24.19	277	564	-29.70	2.68
1988-01	-13.75	918	172	-7.91	315	491	1.60	4.5
2003-12	-13.74	57	1138	-9.32	423	459	19.13	4.37
2009-08	-13.44	842	99	-27.41	259	397	-18.90	3.34
1986-09	-13.13	352	765	-5.24	298	500	37.28	-8.15

Table 8. **Performance of Relative and Absolute Strength Momentum in Different States**

This table presents the performance of relative and absolute strength momentum in three different states. The first state corresponds to months during which there are fewer than 30 absolute losers. The second state corresponds to months during which there are fewer than 30 absolute winners. The third state corresponds to months during which there are at least 30 absolute losers and winners. The tables reports average returns, t-statistics, Sharpe ratios (SR), and number of observations (n) for each state. The sample period is January 1965 to December 2014.

	Abs losers < 30		Abs winners < 30		Abs losers and Abs winners ≥ 30	
	RelMom	AbsMom	RelMom	AbsMom	RelMom	AbsMom
$\bar{R}$	0.45	0.53	-0.73	0.49	2.04	2.32
$t(\bar{R})$					(5.83)	(7.70)
SR					0.23	0.32
n	25	25	27	27	548	548

Table 9. **What Determines Short-Term Return Continuation?**

This table presents results from a time series regression of short-term return continuation on several explanatory variables:

$$\gamma_{1t} = c_0 + c_1 * |diff|_t + c * X_t + e_t. \tag{6}$$

The short-term return continuation γ_{1t} is derived from the following Fama-MacBeth (1973) regression:

$$R_{it} = \gamma_0 + \gamma_1 * R_{t-12,t-2} + v_{it}, \tag{7}$$

where R_{it} is a vector of stock returns at time t and $R_{t-12,t-2}$ is a vector of cumulative stock returns between $t-12$ and $t-2$. The variable $|diff|$ measures the difference at each point in time between the median of the distribution of recent 11-month cumulative returns and the median of the historical distribution of 11-month cumulative returns. The variables in X include the state of the market over the previous 36 months, momentum gap measured as the difference between the 90th and 10th percentiles of the distribution of cumulative stock returns from month $t-12$ to $t-2$, the average and the standard deviation of the distribution of cumulative stock returns from month $t-12$ to $t-2$. The sample period is 1965-2014. The t-statistics are in parentheses.

Panel A: 1965-2014						
Independent Variables						
Intercept	ABS(Diff)	MEANcumret	SDcumret	MomGap	MktState	Adj. R^2
0.01	-0.04	0.02	-0.01	0.00	0.01	0.04
(1.29)	(-2.75)	(1.86)	(-0.67)	(-0.34)	(1.71)	
0.01	-0.06					0.03
(5.05)	(-3.93)					
0.00		0.01				0.00
(2.42)		(1.19)				
0.01			-0.01			0.00
(2.24)			(-1.00)			
0.01				0.00		0.00
(1.64)				(-0.80)		
-0.01					0.02	0.02
(-1.80)					(3.28)	
Panel B: 2000-2014						
Independent Variables						
Intercept	ABS(Diff)	MEANcumret	SDcumret	MomGap	MktState	Adj. R^2
0.01	-0.13	0.06	-0.03	0.02	0.01	0.17
(0.43)	(-4.30)	(2.80)	(-0.86)	(0.57)	(0.64)	
0.02	-0.14					0.11
(3.44)	(-4.78)					
-0.01		0.04				0.04
(-1.24)		(2.59)				
0.00			0.01			0.00
(-0.60)			(0.57)			
-0.01				0.01		0.00
(-0.69)				(0.66)		
-0.02					0.02	0.04
(-2.30)					(2.62)	

Table 10. **Time Series Momentum Portfolio Characteristics**

This table presents monthly characteristics of time series momentum portfolios over two sample periods. The average return, volatility, and alpha are in percent. The alpha and beta are estimated from a full-period time-series regression of each portfolio's excess return on the excess return of the CRSP value-weighted index, HML, and SMB. The portfolios are constructed using common stocks on the NYSE, AMEX and NASDAQ, excluding stocks priced below $1 at the beginning of the holding period. At the beginning of each month t stocks are sorted into two value-weighted portfolios based on their cumulative excess returns over t-12 to t-2 and held for one month. Portfolio TSL consists of stocks with negative cumulative excess returns, while portfolio TSW consists of stocks with positive cumulative excess returns. The strategy that buys time-series winners (TSW) and sells time-series losers (TSL) is presented in the last column. Panels A and B correspond to sample periods 1965-2014 and 2000-2014, respectively.

	Panel A: 1965-2014		
	TSL	TSW	TSW-TSL
$\bar{R}$	0.57	1.04	0.46
$t(\bar{R})$	2.92	5.73	3.83
$\bar{R}$-$\bar{R}_f$	0.16	0.62	0.46
σ	4.81	4.43	2.96
α	-0.37	0.19	0.57
$t(\alpha)$	-4.73	3.52	4.69
β	1.00	0.92	-0.08
SR	0.03	0.14	0.16
	Panel B: 2000-2014		
	TSL	TSW	TSW-TSL
$\bar{R}$	0.33	0.50	0.17
$t(\bar{R})$	0.84	1.62	0.63
$\bar{R}$-$\bar{R}_f$	0.18	0.35	0.17
σ	5.34	4.16	3.53
α	-0.14	0.05	0.19
$t(\alpha)$	-0.91	0.45	0.78
β	1.13	0.82	-0.31
SR	0.03	0.08	0.05

Table 11. **Absolute Strength Momentum vs. Time Series Momentum**

This table reports time-series regressions over the sample period from 1965 to 2014. Portfolio AbsMom corresponds to the strategy that buys absolute winners and sell absolute losers. Portfolio TSMom corresponds to the strategy that buys time-series winners and sells time-series losers. The other variables are the excess market return (MKT) and the value and size factors HML and SMB of Fama and French (1993). The adjusted R^2 of each regression is reported in the last column.

	Independent Variables						
Dependent Variable	Intercept	MKT-RF	HML	SMB	TSMom	AbsMom	Adj. R^2
AbsMom	0.0137				1.77		0.53
	(6.72)				(25.94)		
AbsMom	0.0151	-0.09	-0.04	-0.13	1.61		0.51
	(7.48)	(-1.86)	(-0.61)	(-2.01)	(24.14)		
TSMom	-0.0019					0.30	0.53
	(-2.23)					(25.94)	
TSMom	-0.0018	-0.02	-0.09	0.05		0.31	0.51
	(-1.91)	(-0.73)	(-2.77)	(1.77)		(24.14)	

APPENDIX

Figure A1. **Overlapping Absolute Strength Return Breakpoints**

This figure reports the cumulative return breakpoints for absolute strength winners and losers. The absolute strength winner and loser breakpoints are based on the historical distribution of overlapping 11-month cumulative returns. The cutoffs are determined by the top 10% of that distribution for the winners and the bottom 10% of the distribution for the losers.

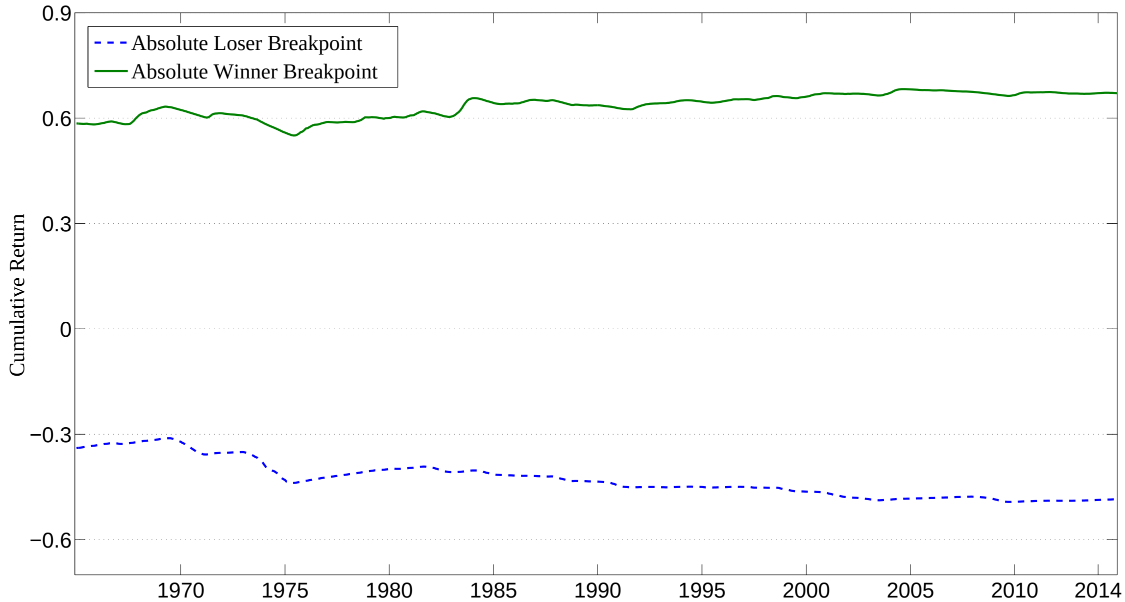


Table A1. **Absolute Strength Portfolio Characteristics: Overlapping Absolute Strength Return Breakpoints**

This table presents monthly characteristics of absolute strength portfolios over two sample periods. The average return, volatility, and alpha are in percent. The alpha and beta are estimated from a full-period time-series regression of each portfolio's excess return on the excess return of the CRSP value-weighted index, HML, and SMB. The absolute strength portfolios are constructed using common stocks on the NYSE, AMEX and NASDAQ, excluding stocks priced below $1 at the beginning of the holding period. At the beginning of each month t, stocks are sorted into value-weighted portfolios based on their cumulative returns over t-12 to t-2 and held for one month. The cumulative return breakpoints are determined based on the historical distribution of overlapping 11-month returns since 1927. The strategy that buys absolute winners and sells absolute losers is presented in the last column. Panels A and B correspond to sample periods 1965-2014 and 2000-2014, respectively.

Panel A: 1965-2014											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\bar{R}$	-0.39	0.14	0.46	0.66	0.64	0.83	0.93	1.06	1.32	1.72	2.15
$t(\bar{R})$	-1.15	0.52	2.10	3.62	3.90	5.13	5.84	6.36	6.70	6.42	7.67
$\bar{R}$-$\bar{R}_f$	-0.80	-0.27	0.05	0.25	0.23	0.42	0.52	0.65	0.91	1.31	2.15
σ	8.34	6.61	5.36	4.44	4.04	3.98	3.90	4.09	4.83	6.57	6.87
α	-1.47	-0.92	-0.46	-0.18	-0.15	0.04	0.14	0.29	0.51	0.88	2.39
$t(\alpha)$	-6.29	-5.55	-4.34	-1.66	-1.60	0.48	1.81	3.35	4.63	5.51	8.47
β	1.20	1.14	0.95	0.84	0.79	0.81	0.78	0.81	0.89	0.97	-0.23
SR	-0.10	-0.04	0.01	0.06	0.06	0.11	0.13	0.16	0.19	0.20	0.31
Cumulative Return (t-12, t-2) Breakpoints											
	10%	20%	30%	40%	50%	60%	70%	80%	90%		
Average	-42.81	-26.30	-14.79	-5.50	2.97	11.91	22.33	36.72	63.59		
Min	-49.27	-30.99	-18.24	-7.97	0.39	8.85	18.54	31.48	55.04		
Max	-31.14	-16.79	-7.26	0.47	7.83	15.76	25.17	38.63	68.25		
SD	5.21	4.03	3.10	2.34	1.79	1.33	1.06	1.45	3.34		

Panel B: 2000-2014											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\bar{R}$	-0.78	0.05	0.26	0.49	0.42	0.56	0.53	0.67	0.70	0.80	1.58
$t(\bar{R})$	-1.05	0.10	0.56	1.41	1.37	1.96	1.90	2.35	1.94	1.55	2.51
$\bar{R}$-$\bar{R}_f$	-0.93	-0.10	0.10	0.33	0.27	0.41	0.38	0.51	0.55	0.64	1.58
σ	9.97	7.49	6.12	4.64	4.14	3.86	3.80	3.84	4.87	6.91	8.44
α	-1.36	-0.47	-0.24	0.11	0.07	0.20	0.17	0.33	0.25	0.26	1.62
$t(\alpha)$	-2.86	-1.42	-0.89	0.57	0.43	1.41	1.17	2.02	1.14	0.85	2.67
β	1.65	1.36	1.12	0.88	0.80	0.78	0.73	0.73	0.86	0.98	-0.67
SR	-0.09	-0.01	0.02	0.07	0.06	0.11	0.10	0.13	0.11	0.09	0.19
Cumulative Return (t-12, t-2) Breakpoints											
	10%	20%	30%	40%	50%	60%	70%	80%	90%		
Average	-48.31	-30.20	-17.58	-7.40	1.75	11.35	22.52	37.98	67.20		
Min	-49.27	-30.99	-18.24	-7.97	1.18	10.76	21.89	37.26	66.09		
Max	-46.32	-29.00	-16.81	-6.91	2.16	11.74	23.01	38.63	68.25		
SD	0.71	0.47	0.35	0.29	0.27	0.27	0.28	0.32	0.49		

Table A2. **Absolute Strength Portfolio Characteristics: NYSE Breakpoints**

This table presents monthly characteristics of absolute strength portfolios over two sample periods. The average return, volatility, and alpha are in percent. The alpha and beta are estimated from a full-period time-series regression of each portfolios excess return on the excess return of the CRSP value-weighted index, HML, and SMB. The absolute strength portfolios are constructed using common stocks on the NYSE, AMEX and NASDAQ. At the beginning of each month t, stocks are sorted into value-weighted portfolios based on their cumulative returns over t-12 to t-2 and held for one month. The cumulative return breakpoints are determined based on the historical distribution of NYSE stock returns. The strategy that buys absolute winners and sells absolute losers is presented in the last column. Panels A and B correspond to sample periods 1965-2014 and 2000-2014, respectively.

Absolute Strength Decile Portfolios											
Panel A: 1965-2014											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\bar{R}$	-0.20	0.29	0.55	0.60	0.75	0.90	0.96	1.11	1.31	1.57	1.80
$t(\bar{R})$	-0.66	1.25	3.01	3.61	4.63	5.63	5.84	6.39	6.30	5.78	7.07
$\bar{R}$-$\bar{R}_f$	-0.61	-0.12	0.14	0.19	0.34	0.49	0.55	0.70	0.90	1.16	1.80
σ	7.41	5.65	4.51	4.09	3.97	3.93	4.02	4.27	5.10	6.66	6.24
α	-1.38	-0.70	-0.32	-0.22	-0.07	0.09	0.16	0.31	0.44	0.68	2.10
$t(\alpha)$	-7.45	-5.01	-3.59	-2.40	-0.85	1.11	1.89	3.19	3.73	4.19	8.27
β	1.22	1.01	0.86	0.79	0.81	0.79	0.79	0.82	0.92	0.99	-0.23
SR	-0.08	-0.02	0.03	0.05	0.08	0.12	0.14	0.16	0.18	0.17	0.29
Panel B: 2000-2014											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\bar{R}$	-0.42	0.28	0.36	0.37	0.45	0.55	0.58	0.73	0.58	0.56	0.98
$t(\bar{R})$	-0.65	0.60	0.99	1.17	1.51	1.94	2.15	2.40	1.57	1.08	1.66
$\bar{R}$-$\bar{R}_f$	-0.57	0.13	0.20	0.22	0.30	0.40	0.43	0.57	0.43	0.41	0.98
σ	8.56	6.24	4.85	4.26	4.01	3.85	3.66	4.07	4.98	7.01	7.89
α	-1.07	-0.26	-0.07	0.00	0.07	0.17	0.25	0.32	0.12	-0.02	1.05
$t(\alpha)$	-2.98	-1.02	-0.37	0.00	0.50	1.23	1.77	1.85	0.54	-0.05	1.87
β	1.58	1.20	0.95	0.84	0.83	0.76	0.72	0.77	0.90	1.01	-0.57
SR	-0.07	0.02	0.04	0.05	0.07	0.10	0.12	0.14	0.09	0.06	0.12

Table A3. **Relative Strength Portfolio Characteristics: NYSE Breakpoints**

This table presents monthly characteristics of relative strength portfolios over two sample periods. The average return, volatility, and alpha are in percent. The alpha and beta are estimated from a full-period time-series regression of each portfolios excess return on the excess return of the CRSP value-weighted index, HML, and SMB. The relative strength portfolios are constructed using common stocks on the NYSE, AMEX and NASDAQ. At the beginning of each month t, stocks are sorted into 10 value-weighted portfolios based on their cumulative returns over t-12 to t-2 and held for one month. Cumulative return breakpoints are based on NYSE firms alone. The strategy that buys relative winners and sells relative losers is presented in the last column. Panels A and B correspond to sample periods 1965-2014 and 2000-2014, respectively.

Relative Strength Decile Portfolios											
Panel A: 1965-2014											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\bar{R}$	0.20	0.69	0.84	0.88	0.82	0.90	0.93	1.10	1.13	1.51	1.31
$t(\bar{R})$	0.59	2.71	3.83	4.44	4.50	4.87	5.12	5.97	5.66	5.92	4.60
$\bar{R}$-$\bar{R}_f$	-0.21	0.28	0.43	0.47	0.41	0.49	0.51	0.68	0.72	1.10	1.31
σ	8.14	6.28	5.39	4.86	4.50	4.54	4.45	4.51	4.90	6.25	6.99
α	-1.08	-0.44	-0.20	-0.10	-0.13	-0.05	0.03	0.20	0.21	0.58	1.67
$t(\alpha)$	-5.52	-3.24	-2.37	-1.16	-1.90	-0.73	0.43	2.77	2.47	4.69	5.89
β	1.38	1.21	1.08	1.02	0.97	0.99	0.96	0.95	1.00	1.03	-0.35
SR	-0.03	0.05	0.08	0.10	0.09	0.11	0.12	0.15	0.15	0.18	0.19
Panel B: 2000-2014											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\bar{R}$	0.32	0.57	0.61	0.81	0.76	0.65	0.67	0.72	0.58	0.67	0.35
$t(\bar{R})$	0.40	1.03	1.34	2.09	2.28	2.04	2.13	2.38	1.71	1.43	0.50
$\bar{R}$-$\bar{R}_f$	0.17	0.42	0.46	0.65	0.61	0.50	0.52	0.57	0.43	0.52	0.35
σ	10.68	7.44	6.17	5.18	4.50	4.31	4.23	4.07	4.57	6.35	9.46
α	-0.47	-0.11	0.02	0.24	0.21	0.11	0.19	0.17	0.07	0.09	0.56
$t(\alpha)$	-1.00	-0.37	0.06	1.39	1.57	0.90	1.25	1.32	0.39	0.34	0.86
β	1.93	1.44	1.21	1.05	0.92	0.89	0.84	0.80	0.88	0.95	-0.98
SR	0.02	0.06	0.07	0.13	0.14	0.12	0.12	0.14	0.09	0.08	0.04

Table A4. **Portfolio Characteristics: 1978-2014**

This table presents monthly characteristics of absolute strength portfolios (Panel A) and relative strength portfolios (Panel B) over the period January, 1978 to December, 2014. The average return, volatility, and alpha are in percent. The alpha and beta are estimated from a full-period time-series regression of each portfolios excess return on the excess return of the CRSP value-weighted index, HML, and SMB. All portfolios are constructed using common stocks on the NYSE, AMEX and NASDAQ, excluding stocks priced below $1 at the beginning of the holding period. At the beginning of each month t, stocks are sorted into 10 value-weighted portfolios based on their cumulative returns over t-12 to t-2 and held for one month. The cumulative return breakpoints for absolute strength portfolios are determined based on the historical distribution of returns since 1978. The cumulative return breakpoints for relative strength portfolios are determined based on the distribution of returns over t-12 to t-2. The strategy that buys winners and sells losers is presented in the last column.

Panel A: Absolute Strength Decile Portfolios											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\bar{R}$	-0.37	0.42	0.52	0.78	0.89	1.07	1.11	1.30	1.49	1.83	2.20
$t(\bar{R})$	-0.89	1.31	2.00	3.73	4.50	5.54	5.78	5.96	5.72	5.40	6.23
$\bar{R}$-$\bar{R}_f$	-0.77	0.02	0.12	0.38	0.49	0.67	0.71	0.90	1.09	1.43	2.20
σ	8.76	6.70	5.47	4.42	4.17	4.07	4.06	4.58	5.48	7.12	7.43
α	-1.74	-0.80	-0.60	-0.20	-0.06	0.11	0.20	0.33	0.45	0.77	2.51
$t(\alpha)$	-6.46	-4.00	-3.80	-1.76	-0.65	1.35	2.41	3.03	3.28	4.36	7.05
β	1.32	1.15	1.00	0.86	0.85	0.85	0.82	0.90	1.00	1.06	-0.26
SR	-0.09	0.00	0.02	0.09	0.12	0.16	0.18	0.20	0.20	0.20	0.30
Panel B: Relative Strength Decile Portfolios											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\bar{R}$	-0.14	0.44	0.68	0.95	1.00	0.93	1.15	1.25	1.27	1.61	1.75
$t(\bar{R})$	-0.30	1.19	2.29	3.80	4.37	4.39	5.50	5.59	5.11	4.84	4.13
$\bar{R}$-$\bar{R}_f$	-0.54	0.04	0.28	0.55	0.60	0.53	0.75	0.85	0.87	1.21	1.75
σ	10.04	7.81	6.29	5.26	4.82	4.48	4.40	4.73	5.24	7.02	8.95
α	-1.72	-0.98	-0.59	-0.22	-0.12	-0.16	0.09	0.19	0.22	0.51	2.23
$t(\alpha)$	-5.39	-4.23	-3.46	-1.74	-1.28	-2.06	1.14	2.07	1.89	3.12	5.28
β	1.58	1.37	1.18	1.06	1.02	0.98	0.95	0.99	0.98	1.06	-0.52
SR	-0.05	0.01	0.04	0.10	0.12	0.12	0.17	0.18	0.17	0.17	0.20

Table A5. **Performance of Relative and Absolute Strength Momentum in Different States: 1978-2014**

This table presents the performance of relative and absolute strength momentum in three different states. The first state corresponds to months during which there are fewer than 30 absolute losers. The second state corresponds to months during which there are fewer than 30 absolute winners. The third state corresponds to months during which there are at least 30 absolute losers and winners. The tables reports average returns, t-statistics, Sharpe ratios (SR), and number of observations (n) for each state. The sample period is January, 1978 to December, 2014.

	Abs losers $<$ 30		Abs winners $<$ 30		Abs losers and Abs winners $\geq$ 30	
	RelMom	AbsMom	RelMom	AbsMom	RelMom	AbsMom
$\bar{R}$	-3.43	0.07	-7.94	0.01	1.94	2.25
$t(\bar{R})$					(4.67)	(6.24)
SR					0.22	0.30
n	4	4	6	6	433	433

Table A6. **Relative Strength Portfolio Characteristics: Jegadeesh and Titman (1993) Portfolios**

This table presents monthly characteristics of relative strength portfolios. Ten portfolios are constructed by ranking stocks based on their relative performance over the past 3, 6, 9, or 12 (J) months and holding them for either 3, 6, 9, or 12 (K) months. Stocks priced below $1 at the beginning of the holding period are excluded. The table reports results for the Loser, Winner, and Winner-Loser portfolios. The average return, volatility, and alpha are in percent. The alpha and beta are estimated from a full-period time-series regression of each portfolios excess return on the excess return of the CRSP value-weighted index, HML, and SMB. Panels A and B correspond to sample periods 1965-2014 and 2000-2014, respectively.

Panel A: 1965-2014												
	J=3, K=3			J=6, K=6			J=9, K=9			J=12, K=12		
	Loser	Winner	W-L	Loser	Winner	W-L	Loser	Winner	W-L	Loser	Winner	W-L
$\bar{R}$	0.49	1.29	0.80	0.27	1.56	1.30	0.36	1.43	1.07	0.63	1.23	0.61
$t(\bar{R})$	1.38	4.62	3.86	0.73	5.52	5.65	1.00	4.98	5.07	1.77	4.30	3.03
$\bar{R}$-$\bar{R}_f$	0.08	0.88	0.80	-0.14	1.15	1.30	-0.05	1.02	1.07	0.21	0.82	0.61
σ	8.74	6.86	5.08	9.00	6.96	5.63	8.78	7.05	5.17	8.67	7.04	4.93
α	-0.92	0.11	1.03	-1.17	0.39	1.57	-1.10	0.28	1.38	-0.86	0.11	0.97
$t(\alpha)$	-5.23	1.12	5.00	-6.00	4.23	6.84	-6.00	3.16	6.71	-4.88	1.28	5.10
β	1.23	0.98	-0.25	1.23	1.01	-0.22	1.20	1.05	-0.15	1.17	1.07	-0.10
SR	0.01	0.13	0.16	-0.02	0.17	0.23	-0.01	0.14	0.21	0.02	0.12	0.12
Panel B: 2000-2014												
	J=3, K=3			J=6, K=6			J=9, K=9			J=12, K=12		
	Loser	Winner	W-L	Loser	Winner	W-L	Loser	Winner	W-L	Loser	Winner	W-L
$\bar{R}$	0.46	1.01	0.55	0.37	1.10	0.72	0.55	0.83	0.28	0.77	0.66	-0.11
$t(\bar{R})$	0.57	1.81	1.03	0.45	1.96	1.22	0.70	1.46	0.55	1.02	1.17	-0.24
$\bar{R}$-$\bar{R}_f$	0.31	0.86	0.55	0.22	0.94	0.72	0.40	0.67	0.28	0.62	0.51	-0.11
σ	10.72	7.52	7.17	11.24	7.51	7.98	10.62	7.61	6.78	10.16	7.64	6.05
α	-0.45	0.06	0.51	-0.60	0.21	0.81	-0.50	0.03	0.53	-0.33	-0.07	0.26
$t(\alpha)$	-1.04	0.30	1.03	-1.23	1.06	1.43	-1.11	0.16	1.07	-0.79	-0.41	0.60
β	1.70	1.01	-0.69	1.71	1.04	-0.67	1.61	1.12	-0.50	1.52	1.18	-0.34
SR	0.03	0.11	0.08	0.02	0.13	0.09	0.04	0.09	0.04	0.06	0.07	-0.02

Table A7. **Absolute Strength Portfolio Characteristics: Jegadeesh and Titman (1993) Portfolios**

This table presents monthly characteristics of absolute strength portfolios. Ten portfolios are constructed by ranking stocks based on their absolute strength performance over the past 3, 6, 9, or 12 (J) months and holding them for either 3, 6, 9, or 12 (K) months. Stocks priced below $1 at the beginning of the holding period are excluded. The table reports results for the Loser, Winner, and Winner-Loser portfolios. The average return, volatility, and alpha are in percent. The alpha and beta are estimated from a full-period time-series regression of each portfolios excess return on the excess return of the CRSP value-weighted index, HML, and SMB. Panels A and B correspond to sample periods 1965-2014 and 2000-2014, respectively.

Panel A: 1965-2014												
	J=3, K=3			J=6, K=6			J=9, K=9			J=12, K=12		
	Loser	Winner	W-L	Loser	Winner	W-L	Loser	Winner	W-L	Loser	Winner	W-L
$\bar{R}$	0.28	1.19	0.92	0.09	1.60	1.52	0.20	1.44	1.24	0.47	1.24	0.77
$t(\bar{R})$	0.83	4.28	5.07	0.25	5.73	7.77	0.57	5.03	6.36	1.36	4.28	4.15
$\bar{R}$-$\bar{R}_f$	-0.13	0.78	0.92	-0.33	1.19	1.52	-0.21	1.03	1.24	0.06	0.83	0.77
σ	8.28	6.84	4.42	8.41	6.85	4.77	8.57	7.02	4.79	8.49	7.11	4.56
α	-1.12	0.00	1.12	-1.30	0.45	1.76	-1.27	0.29	1.56	-1.01	0.11	1.12
$t(\alpha)$	-6.97	-0.01	6.25	-7.33	4.28	9.13	-7.32	3.05	8.33	-5.95	1.16	6.47
β	1.17	1.01	-0.16	1.15	1.01	-0.14	1.17	1.07	-0.10	1.15	1.09	-0.06
SR	-0.02	0.11	0.21	-0.04	0.17	0.32	-0.02	0.15	0.26	0.01	0.12	0.17
Panel B: 2000-2014												
	J=3, K=3			J=6, K=6			J=9, K=9			J=12, K=12		
	Loser	Winner	W-L	Loser	Winner	W-L	Loser	Winner	W-L	Loser	Winner	W-L
$\bar{R}$	0.02	0.99	0.97	-0.06	1.04	1.10	0.16	0.82	0.66	0.40	0.67	0.27
$t(\bar{R})$	0.02	1.82	2.30	-0.09	1.90	2.38	0.23	1.49	1.60	0.58	1.20	0.70
$\bar{R}$-$\bar{R}_f$	-0.13	0.83	0.97	-0.22	0.89	1.10	0.01	0.67	0.66	0.25	0.52	0.27
σ	9.46	7.30	5.66	9.76	7.36	6.20	9.64	7.41	5.56	9.41	7.51	5.09
α	-0.91	0.03	0.94	-1.03	0.15	1.18	-0.87	0.00	0.87	-0.68	-0.12	0.56
$t(\alpha)$	-2.51	0.18	2.33	-2.58	0.75	2.59	-2.24	-0.02	2.12	-1.82	-0.67	1.51
β	1.51	1.06	-0.45	1.49	1.07	-0.43	1.45	1.14	-0.31	1.41	1.19	-0.21
SR	-0.01	0.11	0.17	-0.02	0.12	0.18	0.00	0.09	0.12	0.03	0.07	0.05

Table A8. **Portfolio Characteristics: Not Skipping a Month between Ranking and Holding Periods**

This table presents monthly characteristics of absolute strength and relative strength portfolios over two sample periods. The average return, volatility, and alpha are in percent. The alpha and beta are estimated from a full-period time-series regression of each portfolios excess return on the excess return of the CRSP value-weighted index, HML, and SMB. All portfolios are constructed using common stocks on the NYSE, AMEX and NASDAQ, excluding stocks priced below $1 at the beginning of the holding period. At the beginning of each month t, stocks are sorted into 10 value-weighted portfolios based on their cumulative returns over t-12 to t-1 and held for one month. The cumulative return breakpoints for absolute strength portfolios are determined based on the historical distribution of returns. The cumulative return breakpoints for relative strength portfolios are determined based on the distribution of returns over t-12 to t-1. The strategy that buys winners and sells losers is presented in the last column.

Panel A: 1965-2014											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Absolute Strength Decile Portfolios											
$\bar{R}$	-0.26	0.36	0.58	0.68	0.72	0.84	1.03	1.16	1.31	1.60	1.90
$t(\bar{R})$	-0.77	1.42	2.82	3.91	4.53	5.39	6.22	6.64	6.32	5.92	6.79
$\bar{R}$-$\bar{R}_f$	-0.67	-0.05	0.17	0.26	0.31	0.43	0.62	0.75	0.89	1.19	1.90
σ	8.36	6.33	5.07	4.23	3.93	3.84	4.08	4.30	5.07	6.65	6.85
α	-1.39	-0.66	-0.32	-0.15	-0.07	0.05	0.23	0.39	0.49	0.78	2.21
$t(\alpha)$	-6.20	-4.21	-3.18	-1.62	-0.90	0.71	2.94	4.28	4.15	4.95	7.90
β	1.26	1.11	0.93	0.84	0.81	0.80	0.83	0.84	0.92	0.99	-0.27
SR	-0.08	-0.01	0.03	0.06	0.08	0.11	0.15	0.17	0.18	0.18	0.28
Relative Strength Decile Portfolios											
$\bar{R}$	-0.08	0.40	0.66	0.79	0.82	0.87	0.96	1.08	1.18	1.50	1.58
$t(\bar{R})$	-0.21	1.29	2.53	3.59	4.16	4.77	5.23	5.73	5.62	5.44	4.52
$\bar{R}$-$\bar{R}_f$	-0.50	-0.01	0.25	0.38	0.41	0.46	0.55	0.67	0.77	1.08	1.58
σ	9.88	7.61	6.40	5.42	4.86	4.50	4.52	4.65	5.17	6.74	8.57
α	-1.46	-0.82	-0.45	-0.24	-0.17	-0.08	0.04	0.18	0.28	0.59	2.05
$t(\alpha)$	-5.76	-4.55	-4.53	-2.34	-2.29	-1.29	0.69	2.54	2.98	4.20	6.00
β	1.55	1.34	1.20	1.09	1.04	0.98	0.97	0.97	0.98	1.01	-0.54
SR	-0.05	0.00	0.04	0.07	0.08	0.10	0.12	0.14	0.15	0.16	0.18
Panel B: 2000-2014											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Absolute Strength Decile Portfolios											
$\bar{R}$	-0.66	0.16	0.46	0.47	0.48	0.49	0.62	0.73	0.65	0.59	1.24
$t(\bar{R})$	-0.86	0.28	1.05	1.41	1.67	1.88	2.22	2.55	1.76	1.13	1.92
$\bar{R}$-$\bar{R}_f$	-0.81	0.00	0.31	0.32	0.33	0.34	0.47	0.58	0.50	0.43	1.24
σ	10.22	7.34	5.91	4.47	3.89	3.51	3.76	3.88	5.00	6.99	8.70
α	-1.27	-0.36	0.00	0.06	0.13	0.16	0.26	0.35	0.22	0.08	1.36
$t(\alpha)$	-2.60	-1.12	0.00	0.40	0.97	1.35	1.85	2.17	0.95	0.27	2.18
β	1.69	1.35	1.11	0.90	0.79	0.72	0.74	0.73	0.88	0.99	-0.70
SR	-0.08	0.00	0.05	0.07	0.08	0.10	0.12	0.15	0.10	0.06	0.14
Relative Strength Decile Portfolios											
$\bar{R}$	-0.09	0.34	0.64	0.60	0.57	0.67	0.60	0.65	0.49	0.57	0.66
$t(\bar{R})$	-0.10	0.47	1.09	1.31	1.51	2.05	2.02	2.08	1.40	1.09	0.75
$\bar{R}$-$\bar{R}_f$	-0.25	0.19	0.48	0.45	0.42	0.52	0.45	0.50	0.34	0.41	0.66
σ	13.12	9.60	7.83	6.16	5.10	4.39	4.04	4.25	4.72	6.97	11.84
α	-0.90	-0.35	-0.02	0.03	0.02	0.13	0.12	0.13	-0.05	-0.02	0.88
$t(\alpha)$	-1.48	-0.87	-0.07	0.13	0.13	1.21	1.11	0.99	-0.26	-0.08	1.12
β	2.27	1.79	1.46	1.24	1.07	0.93	0.85	0.85	0.83	0.92	-1.35
SR	-0.02	0.02	0.06	0.07	0.08	0.12	0.11	0.12	0.07	0.06	0.06