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Time Series Momentum Implemented

Testing the Performance of Long-Only Time Series Momentum Strategies from the Perspective of an Individual Investor, Accounting for Strategy Costs

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ABSTRACT

Moskowitz, Ooi, and Pedersen (2012) develop a time series momentum (TSMOM) strategy that uses the sign of an asset's mean excess return over a lookback horizon of 12 months to determine its trend signal. The strategy takes long positions in assets with positive signals and short positions in assets producing negative signals. They find that the strategy realizes abnormal excess returns. These results do not, however, account for costs associated with strategy execution. Related studies that do account for costs, are conducted from the perspective of institutional investors. Finally, the use of shorting in the strategy may not be a viable option for some individual investors. Hence, many of the findings documented in the literature are of little practical utility to individual investors. Therefore, this paper seeks to discover the degree to which an individual investor can realize portfolio performance that outperforms traditional investment strategies, by implementing a long-only TSMOM strategy that accounts for real-life costs.

For use throughout the analysis, the paper develops two long-only TSMOM strategies termed the levered TSMOM (LTSMOM) strategy and the unlevered TSMOM (UTSMOM) strategy. In both cases, when an asset has a negative trend signal it is excluded from the portfolio, rather than shorted. Moreover, the new strategies account for transaction and financing costs in the calculation of their returns.

Using data from 15 equity index and 6 bond index ETFs between January 2004 and October 2019, the paper performs a pooled panel autoregression and finds significant price continuation in the data. Comparing a broad set of performance measures across strategies and lookback horizons, the paper discovers a lookback horizon of 3 months to produce the best results for both the LTSMOM and the UTSMOM strategy. Furthermore, the paper finds that using 3-month lookback horizons, the strategies outperform identically constructed strategies that do not use time-series momentum signals, emphasizing that the use of these signals enhances investment performance. Testing the impact of costs on the strategies, the paper finds that both the LTSMOM and UTSMOM strategies are robust to transaction costs. However, the paper determines that the LTSMOM strategy is unsuitable for implementation due to its significant decline in performance, caused by financing costs. The paper finds that the UTSMOM strategy is robust to expense ratio costs specific to ETFs, indicating that the asset class is suitable for use in the strategy. Finally, the paper compares the performance measures of the LTSMOM and UTSMOM strategies to two standard asset allocation strategies. The paper finds that the UTSMOM strategy exhibits a considerably higher Sharpe ratio than the other strategies and displays superior risk measures. Moreover, the UTSMOM strategy realizes a statistically significant alpha, presenting a challenge to standard rational asset pricing theory.

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1 INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

The *Efficient Market Hypothesis* (EMH) states that prices reflect all relevant and currently available information. The theory implies that assets are priced correctly based on extant information and only new information can drive changes in prices (Fama, 1970). Therefore, under the EMH, it should be impossible to predict future movements in asset prices except as rational compensation for risk, since all available information is already incorporated into the asset's price. Hence, asset prices are said to follow a *random walk.* The EMH asserts that since historical asset price data are publicly available at little or no cost, investors would utilize the apparent signals concerning future performance and react accordingly. Thus, the information would be priced-in instantaneously, causing an immediate price-change, rendering the future predictability of asset prices based on this information impossible. A great deal of financial and economic theory relies on the fact that markets are efficient. For instance, the capital asset pricing model (CAPM) asserts that investors are rational and have homogenous expectations.

Though popular, the EMH and CAPM theory have not remained unchallenged. Studies performed Black, Jensen, and Scholes (1972), Frazzini and Pedersen (2014) and Asness et al. (2012) find statistically significant evidence that the empirical security market line (SML) associated with the CAPM is flatter than theory would suggest. This means that risk-adjusted returns are larger for safer assets than risky ones. This insight led Asness et al. (2012) to perform an empirical study whereby they document that leveraging portfolios that are more concentrated in safer assets leads to superior performance compared to those that overweight riskier assets. Specifically, they leverage a risk parity portfolio which is an equally weighted portfolio, where weights refer to risk rather than the amount of wealth invested in each asset. Against this background they argue that the empirically flat SML can be explained by leverage aversion, whereby investors are either unable or unwilling to use leverage to increase returns. The authors argue that this causes investors to overweight risky assets with the aim of realizing greater returns causing the SML to become flatter.

Theories presented within the realm of Behavioural Finance have challenged the EMH by questioning the central assumption of rationality and the idea that new information is priced in immediately. Shefrin and Statman (1985) present the argument that a behavioural pattern exists whereby investors have a disposition to sell well-performing stocks (winners) too early and hold on to poorly-performing stocks (losers) for too long. Daniel, Hirshleifer and Subrahmanyam (1998) find that positive return autocorrelations can be caused by an ongoing overreaction to a certain event. The arguments presented by the scholars challenge the traditional view that securities are priced in a rational manner using rational asset pricing models that reflect all publicly available information.

With an offset in behavioural theories Jegadeesh and Titman (1993) were able to empirically document momentum profits for the first time. Through analysing data on a wide range of stocks over a period ranging from 1965 to 1989, Jegadeesh and Titman find that momentum trading strategies where an investor bets on past winners, also known as relative strength trading strategies do realize significant abnormal returns. More recent research on time-series momentum has been performed by Moskowitz, Ooi and Pedersen (2012), who study a broad set of data, consisting of futures returns from January 1965 to December 2009. Moskowitz et al. (2012) develop a methodology to construct portfolios based on what they coin the *Time Series Momentum* (TSMOM) factor. This strategy uses the sign of an asset's mean excess return over the most recent 12 months to identify its trend signal. The strategy holds long positions in assets that produce positive signals and short positions in assets with negative signals. Inherent in the construction of the TSMOM portfolios is the use of the volatility scaling and leverage. That is, each position is scaled to produce an ex ante volatility of 40%, effectively leveraging the positions. The TSMOM strategy is therefore a form of levered risk parity portfolio. Testing the TSMOM strategy, the authors find that it produces abnormal excess returns, which questions the assumptions of the EMH. A more recent study, conducted by Hurst, Ooi, and Pedersen (2017) finds that clear trends have been absent and trend-following strategies have produced mixed results in recent years. However, the authors argue that this may be due to the current economic environment which may change to the benefit of trend-following strategies in the future. Moreover, Hurst et al. (2017) find evidence that trend-following strategies produce attractive diversification benefits in current market conditions.

Though much of the literature on momentum provides encouraging evidence of significant abnormal returns, it has not been without challenge or criticism. Korajczyk and Sadka (2004) find evidence that suggests transaction costs significantly reduce the level of abnormal returns obtained by momentum strategies. Lesmond, Schill, and Zhou (2004) also find evidence that transaction costs completely eliminate all the apparent abnormal returns generated by momentum strategies. Moreover, they find that most of the profits from momentum strategies are provided by the short positions. They argue that short-selling past losers entails disproportionately high trading costs and thus renders the strategies useless in a real world setting. Finally, Kim, Tse, and Wald (2016) direct criticism specifically towards the TSMOM strategy developed by Moskowitz et al. (2012). They argue that the impressive performance of the strategy derives mainly from the use of volatility scaling which causes the TSMOM strategy to be leveraged by construction. Finally, studies that account for costs in momentum strategies tend to do so from the perspective of institutional investors, both explicitly and implicitly. Therefore, individual investors interested in implementing a TSMOM strategy have little guidance regarding the profitability of the strategy when accounting for its costs.

With an offset in the TSMOM strategy developed by Moskowitz et al. (2012), this paper seeks to shed light on the criticisms of time-series momentum, conducting an empirical analysis that aims to generate results that resemble real-life strategy implementation as much as possible. Moreover, to broaden the discussion of time series momentum, this paper focuses on strategy implementation from the perspective of an individual investor. Therefore, rather than analysing futures contracts which must be rolled when they near expiry, this paper analyses exchange traded funds (ETF) which are less complicated and thus perhaps better suited to an individual investor. With many individual investors unable or unwilling to engage in the short-selling of assets and drawing on the insights of Lesmond et al. (Lesmond et al., 2004) regarding higher transaction costs for short positions, this paper assumes no short-selling. To address the criticism of Kim et al. (2016) while still seeking to extract the benefits of leverage presented by Asness et al. (2012), the paper develops two new TSMOM strategies, the levered TSMOM (LTSMOM) strategy and the unlevered TSMOM (UTSMOM) strategy. Furthermore, the paper creates all-long versions of the two strategies that ignore trend signals, termed the levered risk parity (LRP) strategy and the unlevered risk parity (URP) strategy. Including these all-long strategies in the analysis enables the paper to directly observe whether time series momentum enhances strategy performance. The levered strategies incorporate financing and transaction costs into their calculation, whereas the unlevered strategies, not subject to leverage, account only for transaction costs. Assuming no short-selling and accounting for relevant costs, these extensions to the TSMOM theory aid in answering the research question which is now presented.

1.2 Research Question

This paper aims to uncover whether it is possible to implement an investment strategy that both exploits the existence of return continuation and the higher risk-adjusted returns associated with safer assets, from the perspective of an individual investor. To this end, it will seek to answer the research question:

To what extent is it possible for an individual investor to realize superior portfolio performance compared to traditional investment strategies by implementing a long-only time-series momentum strategy that controls volatility and accounts for real-life strategy costs?

Due to the length and complexity of the analysis at hand, the paper will answer a set of smaller, more approachable questions, that together provide an answer to the main research question.

An important factor in terms of this paper's analysis is whether the data displays evidence of return continuation. Without the presence of return continuation in the data the implementation of a time series momentum strategy would make little sense. Moskowitz et al (2012) use 12 months of return data to determine the signals used in their TSMOM strategy. While the authors find this lookback horizon to be optimal in the data they analyse, this is not necessarily the case for the data used in this analysis. The signal used in the time series momentum strategies may have a significant impact on their performance. Therefore, finding the appropriate lookback horizon to calculate the time-series momentum signals is essential. The paper will therefore seek to answer the following question:

1. *Is there evidence of return continuation in the data and what is the optimal look-back horizon to use for the long-only momentum signals in terms of producing the best performance?*

While a paper portfolio may produce attractive performance measures, the real-life implementation of any trading strategy is subject to transaction costs. Therefore, the paper must answer the following question:

2. *To what extent are the developed time-series momentum strategies robust to the trading costs an individual investor would be subject to?*

Leveraged strategies will be subject to financing costs. In much of the literature, this is stated to be the risk-free rate. Whereas it may be possible to borrow at the risk-free rate for a large institutional investor, this is most likely not be the case for an individual investor, who will be subject to higher financing costs. To this end, the following question must be answered:

3. *To what degree is the leveraged time-series momentum strategy robust to the financing costs that an individual investor is exposed to?*

The paper performs the analysis using ETFs which are subject to costs known as expense ratios. Seeking to conduct an analysis that provides results that resemble real-life strategy implementation as much as possible, the paper must account for these costs. Furthermore, this will provide valuable insights as to whether these instruments are suited to such a strategy. Therefore, the paper will answer the question:

4. *To what extent are the developed time-series momentum strategies robust to the expense ratio costs associated with ETFs and considering these are ETFs suitable instruments for the strategies?*

Even if the time-series momentum strategies do produce positive performance measures, these may simply be caused by the risk parity method of asset allocation. It is therefore important to observe the effect that using time-series signals has on the performance measures. To this end it is useful to compare the performance measures of the time-series momentum strategies with their risk parity counterparts. That is portfolios that use the same asset allocation principles but where the use of momentum signal is absent. Following this path, the question must be answered:

5. *Given the costs associated with the real-life implementation of the time-series momentum strategies, to what extent do they produce performance measures over and above those of all-long, otherwise identical, risk parity strategies?*

Finally, even if the time-series momentum strategies do produce positive performance results it is desirable to contextualize these. That is, it is of interest to know whether they outperform other, simpler strategies. Hence, the last question that must be answered is the following:

6. *Accounting for all costs, do time-series momentum strategies perform better than other standard asset allocation strategies?*

Having presented the research question and its underlying sub-questions, the paper will now proceed to describe how it contributes to the existing literature.

1.3 CONTRIBUTION TO THE LITERATURE

This paper contributes to the existing literature in several ways. It will take its point of departure in the TSMOM strategy developed by Moskowitz et al. (2012) with a number of alterations. The changes made to the TSMOM strategy are mainly driven by the criticism that that it has received. Addressing these issues provides additional insights into the dynamics and performance of the strategy. First, to address the criticism presented by Lesmond et al. (2004) regarding TSMOM profits being driven by short positions with high trading costs, the paper implements a long-only TSMOM strategy. By conducting an isolated test of long-only strategies the paper provides clear and dedicated results regarding their performance, as opposed to decomposing long-short strategies to extract performance measures, as has been the case previously. Second, levered and unlevered versions of the TSMOM strategy are developed. This addresses the criticism of Kim et al. (2016) who claim that TSMOM performance is driven by leverage. Creating a formula dedicated to testing an unlevered TSMOM strategy as opposed to simply deleveraging the original TSMOM strategy provides a new perspective to the literature. Third, the paper further extends the original TSMOM formula to account for trading and financing costs. This extension is practical and simple to use, facilitating a more complete and realistic way to test the performance of the strategy. This contributes to the discussion on whether the TSMOM strategy is robust to trading costs, as well as broadens the discussion to encompass the effects of financing costs associated with the levered TSMOM strategy. Moreover, subjecting the levered TSMOM strategy to financing costs adds perspective to the leverage aversion theory. Moskowitz et al. (2012) test a broad set of asset classes including equity index futures, commodity futures, bond futures and currency forwards. As far as knowledge extends, ETFs have never been investigated in a time-series momentum context. Therefore, analysing this specific asset class contributes to the existing literature by broadening the scope asset classes that have been investigated for time series momentum characteristics.

1.4 DELIMITATIONS

One of the central elements of this paper is to assess the performance of time-series momentum strategies accounting for transaction costs. However, the paper is unable to gain access to empirical bid-ask transaction costs, since these would vary from minute to minute at any given point during a day. Furthermore, as will be elaborated on in Section 3.1 it has not been possible to access reliable and consistent data on bid and ask prices for the data, with platforms such as Bloomberg and CapitalIQ having large gaps in the data as well as presenting some suspicious results. Nonetheless, using a transaction cost modelling technique developed by Corwin and Schultz (2012) which uses daily high and low prices it is possible to estimate bid-ask transaction costs.

Another focus of the paper is to uncover how the levered strategies perform when accounting for financing costs. In this case, the paper only accounts for the direct costs of borrowing. Specifically, the paper integrates the interest rate cost that an individual investor would have to have to pay in order to use leverage. However, the paper does not account for issues such as margin calls that may have a large influence on the performance of a strategy and with great likelihood require the investor to consider prior to portfolio construction. Addressing this issue is beyond the scope of this paper. However, the paper does provide performance measures such as the maximum drawdown. Although this measure does not inform us whether a margin call would be issued, it does provide some insights regarding the possibility of margin calls during the sample period. Furthermore, funding liquidity is ignored. That is, that paper assumes that the investor has access to external funding at all times.

Finally, the paper does not account for taxes that would be incurred through strategy implementation. To account for taxes on capital gains and dividends would overcomplicate the analysis to a degree that would draw too much attention away from the focus points of the analysis. While the inclusion of taxes would enrich the results, the paper deems this beyond the scope of the analysis.

1.5 OUTLINE

The structure of the paper is as follows. Section 2 presents an in-depth account of the theory that is used in the paper. Furthermore, the it includes this paper’s contribution to the TSMOM theory. Specifically, it is in this chapter that the paper derives the LTSMOM and UTSMOM strategies including the way financing and transaction costs are derived. In Section 3, the paper describes the data that is used in the analysis and conducts preliminary data preparation procedures. Section 4 provides a detailed account of the methodology that is used to conduct the analysis. The paper conducts the analysis in Section 5. Having the results of the analysis Section 6 of the paper discusses the findings and provides answers to the sub-question presented above, eventually providing an answer to the research question. Finally, Section 7 presents a brief collection of recommendations to further research.

2 THEORY

This section of the paper follows a linear path, where each theory that is presented facilitates a greater understanding of the theory that follows. Section 2.1 presents fundamental financial theory that provides a context for the more contemporary theory used in the paper. Following this, Section 2.2 describes the underlying theory of the risk parity asset allocation method which plays a significant role in the construction of the TSMOM strategy and the LTSMOM and UTSMOM strategies that this paper develops. This section also presents a theory of leverage aversion that advocates applying leverage to a risk parity portfolio in order to realize risk-adjusted returns beyond what is possible using traditional asset allocation strategies. Section 2.3 presents a thorough account of the TSMOM theory pioneered by Moskowitz et al. (2012). Finally, the paper develops its contribution to the TSMOM theory in Section 2.4. Specifically, the paper derives the LTSMOM and UTSMOM strategies and describes how financing and transaction costs are calculated.

2.1 MODERN PORTFOLIO THEORY AND THE CAPM

While the paper will not make use of mean-variance analysis as such, the underlying theory regarding the importance of diversification, and a selection of the models pertaining to this theory are of relevance to the methods that will be used in the analysis. For this reason, the paper will provide a brief presentation of modern portfolio theory (MPT) pioneered by Markowitz (1952, 1959).

The underlying assumption of mean-variance analysis is that, when selecting a portfolio of assets, an investor is only concerned about the expected return and variance of the portfolio over a desired future timeframe (Markowitz, 1952). More specifically, the investor who is a *mean-variance optimizer* desires the highest possible expected return given the lowest possible variance of returns.

Given a selection of risky assets, a portfolio constructed hereof is classified as mean-variance efficient if it displays the lowest return variance compared to all other possible portfolio constructions using the same assets that have the same expected return (Markowitz, 1959). Since there are different combinations of asset allocations that will provide a variety of expected return and variance combinations, there exists more than one efficient portfolio depending on the investors willingness to take on risk. The array of possible risk-return combinations forms a parabola, known as the mean-variance frontier. Of these possible portfolios one has received particular focus in the finance literature, namely the minimum-variance portfolio. This is the portfolio that displays the minimum variance among all portfolios with respect to the universe of assets being analysed (Munk, 2018). Portfolios below the minimum-variance portfolio are not optimal. That is, there exist portfolios with higher expected returns given the same standard deviation.

The development of the two-fund separation theorem by Tobin (1958) adds a new dimension to mean-variance frontier. This theorem advocates first selecting the optimal portfolio of risky assets and then combining this risky portfolio with an investment in the risk-free asset. When the risk-free asset is included in the possible portfolio combinations a new efficient frontier is created, not just for risky assets, but for all assets. Whereas the efficient frontier for risky assets produces a parabola, the efficient frontier for all assets manifests as a straight line as shown in Figure 2.1. This line is often referred to as the *capital allocation line* (CAL) (Munk, 2018). The point at which the efficient frontier for all assets meets the efficient frontier for risky assets only is known as the tangency portfolio.

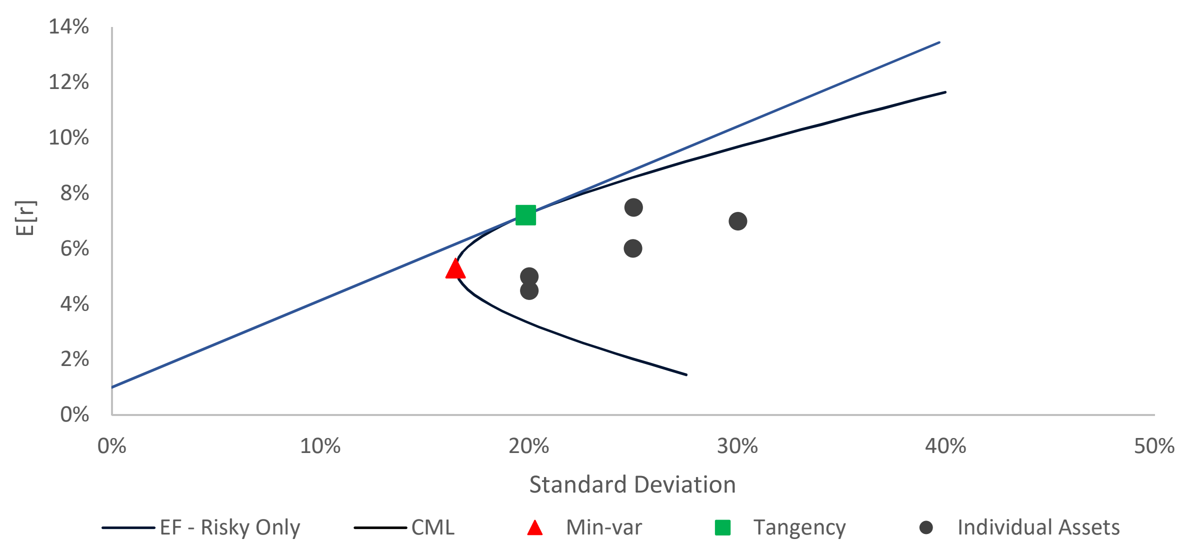


Figure 2.1 A stylized illustration of the efficient frontier and capital allocation line

As is clear from Figure 2.1, the inclusion of the risk-free asset in the portfolio presents the investor with superior risk-return options than the portfolio with risky assets only. The tangency portfolio is the point at which no weight is allocated to the risk-free asset. The further an investor moves left from the tangency portfolio along the CAL, the more weight he allocates to the risk-free asset in the portfolio. An investor who only invests in the risk-free asset has his portfolio where the CAL meets the Y-axis and therefore has a standard deviation of 0%. Conversely, if the investor holds a portfolio to the right of the tangency portfolio, he is borrowing money to leverage his position in the risky assets. The benefits of leverage are easily deduced from Figure 2.1. For instance, at a standard deviation of 30% the expected return is larger for the leveraged portfolio than that of the best possible portfolio that is obtainable from investing only risky assets without the use of leverage.

The Sharpe ratio (SR), named after the economist who developed it, William F. Sharpe (1966), measures the risk adjusted return of a portfolio and has the formula:

$$\frac{\mu - r_f}{\sigma} \tag{2.1}$$

where the numerator consists of the excess return of the portfolio and the denominator is the portfolio standard deviation. The SR depicts the amount of return that an investor will be compensated with given the risk undertaken. A mean-variance optimizer seeks to maximize the SR of his investment. The slope of the CAL is precisely the maximum SR. Therefore, such an investor will construct his portfolio such that it is located somewhere on the CAL (Munk, 2018).

Whereas MPT assumes that mean-variance optimizers construct portfolios so that they are placed somewhere on the CAL, the capital asset pricing model (CAPM) extends this assumption to include all investors (Asness et al., 2012). The CAPM, therefore asserts that the tangency portfolio, as described above, is in fact the market portfolio. The market portfolio is defined as the value-weighted portfolio of all assets. In the case of the market portfolio, the CAL then becomes the capital market line (CML). The slope of the CML is therefore the SR of the market portfolio (Munk, 2018). By path of some derivation, drawing on insights from the two-fund separation theorem, the theoretical CAPM equation is derived as:

$$E[r_i] - r_f = \beta_i\left(E[r_m] - r_f\right) \tag{2.2}$$

where

$$\beta_i = \frac{Cov[r_i, r_m]}{Var[r_m]}$$

Here, $E[r_i]$ represents the expected rate of return of an asset i, $E[r_m]$ is the expected rate of return of the market portfolio and β_i is the market beta of the asset i. According to the CAPM, since all investors hold the market portfolio, the only important risk measure is the asset's beta. Beta represents a stocks systematic risk i.e. the risk that cannot be diversified away. A stylized representation of the relationship between beta and expected return is shown in Figure 2.2. The line in this illustration is the Security Market Line (SML), where the slope of the line is the market risk premium.

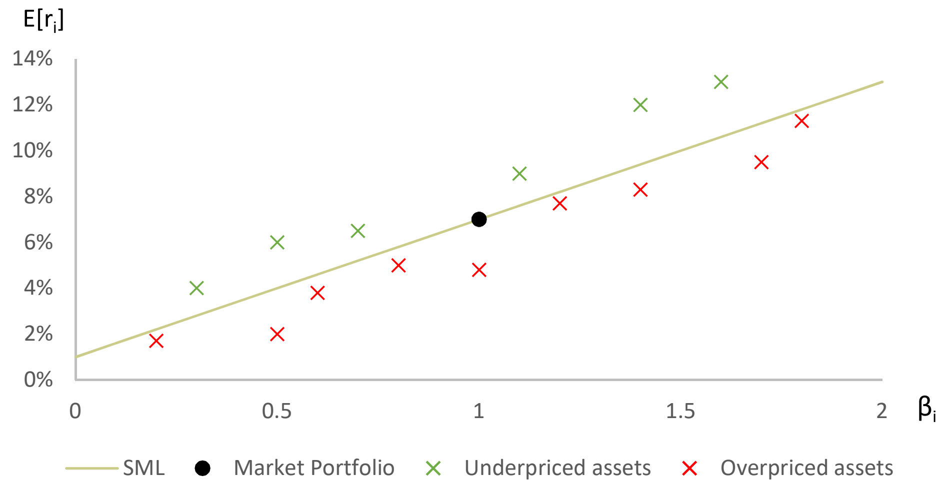


Figure 2.2 A stylized representation of the Security Market Line (SML)

The theoretical CAPM can be, and has been, tested. Performing a linear regression of historical excess returns of a portfolio (or asset) against the market excess returns the empirical CAPM takes the form:

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \varepsilon_{it} \tag{2.3}$$

The estimates of α_i and β_i take the values that minimize the sum of squared residuals. For the CAPM to hold, the estimate of α_i should not be statistically different from zero (Munk, 2018). Figure 2.2 provides an illustration of assets that have an alpha that is not zero. The vertical distance between an individual asset and the SML is its alpha. A great deal of empirical studies have been conducted over many years that find consistent and statistically significant evidence that the empirical SML is flatter than the theoretical CAPM implies including studies performed by Black, Jensen, & Scholes (1972), Frazzini & Pedersen (2014) and Asness et al. (2012). These findings suggest that assets with lower risk provide higher risk-adjusted returns than those with higher risk and creates the point of departure for the paper in terms of asset allocation. Theoretical arguments will now be presented that, according to the proponents of them, enable investors to exploit the shortcomings of the CAPM in order to realize abnormal excess returns.

2.2 Risk Parity and Leverage Aversion

2.2.1 Risk Parity

Three types of budgeting approaches exist in asset allocation - performance budgeting, weight budgeting and risk budgeting (Roncalli, 2014). A mean-variance portfolio that targets a specific expected return is an example of a performance budgeting approach. While the process of efficiently allocating wealth using mean-variance optimization appears attractive and simple, it has some significant drawbacks. To begin with, mean-variance optimized portfolios have a proclivity to be overly concentrated in a small portion of the full range of assets being analysed (Maillard, Roncalli, & Teiletche, 2009). Furthermore, the optimization process causes mean-variance solutions to be excessively sensitive to the expected returns input parameter. That is, small changes in expected returns can cause large transformations in the construction of the portfolio. While the minimum variance portfolio, mentioned above, does not integrate expected returns into its calculation, it still suffers from excessive portfolio concentration (Maillard et al., 2009). The equally-weighted portfolio is an example of weight budgeting. By construction, this approach eliminates the inconvenience of excessive portfolio concentration. However, equally-weighted portfolios, in many instances, suffer from the under-diversification of risk. Risk parity (RP) is an example of a risk budgeting approach. The essence of RP is that asset weights are allocated based on their level of ex-ante risk. Roncalli (2014) argues that this approach to asset allocation does not suffer from excessive portfolio concentration nor the under-diversification of risk.

Roncalli (2014) denote the risk measure of a given portfolio as $\mathcal{R}(x)$ and stipulate properties that $\mathcal{R}(x)$ must satisfy in order to be appropriate to use in relation to the risk allocation principle. These are divided into two subcategories – coherency and convexity. Artzner, Delbaen, Eber, and Heath (1999) outline four properties that must hold if $\mathcal{R}(x)$ is to be considered coherent:

1. Subadditivity

$$\mathcal{R}(x_1 + x_2) \leq \mathcal{R}(x_1) + \mathcal{R}(x_2)$$

   Adding the risk of the two portfolios separately will be more than the risk of the two portfolios together.

2. Homogeneity

$$\mathcal{R}(\lambda x) = \lambda \mathcal{R}(x) \quad \text{if} \quad \lambda \geq 0$$

   If the portfolio is subject to leveraging or deleveraging, its risk measure will increase or decrease by the same scale.

3. Monotonicity

$$if\ x_1 \prec x_2, then\ \mathcal{R}(x_1) \geq \mathcal{R}(x_2)$$

If, under all scenarios, portfolio x_2 displays a superior return compared to that of x_1 then risk measure $\mathcal{R}(x_2)$ should be lower than $\mathcal{R}(x_1)$.

4. Translation invariance

$$if\ m \in \mathbb{R}, then\ \mathcal{R}(x+m) = \mathcal{R}(x) - m$$

The addition of cash, m, to the portfolio will result in the reduction of risk by m.

Believing that the first two axioms of coherency are too strong, Föllmer & Schied (2002) develop a weaker convexity condition which they argue should replace them.

$$\mathcal{R}(\lambda x_1 + (1-\lambda)x_2) \leq \lambda\mathcal{R}(x_1) + (1-\lambda)\mathcal{R}(x_2)$$

Simply put, the convexity condition requires that combining two portfolios should not surpass the combined risk of the individual portfolios. That is, diversification must not increase risk.

Roncalli (2014) shows that standard deviation (SD) as a risk measure satisfies the coherency and convexity conditions, except for the translation invariance axiom. Nonetheless, the author argues that this axiom is designed for purposes other than portfolio management and is poorly designed for this discipline. For this reason, he argues that SD can comfortably be considered a coherent and convex risk measure.

2.2.2 Leverage Aversion and the Flat Security Market Line

Having provided a brief presentation of some of the underlying ideas of risk parity, the paper will now draw on an empirical study conducted by Asness, Frazzini, and Pedersen (2012) where both levered and unlevered RP portfolios are created and compared to various other portfolios. While this paper is of great utility from a practical perspective, it also sheds some light on the shortcomings of the CAPM, placing particular focus on the flatness of the security market line and providing a theory that seeks to explain this empirical observation. The paper will first describe the risk parity formulae that Asness et al. (2012) use to construct their RP portfolios. Following this, the empirical finding of the study will be presented.

The authors define the weight allocations of assets in their RP portfolios as

$$w_{t,i} = k_t \hat{\sigma}_{t,i}^{-1}, \tag{2.4}$$

where $i = 1, \dots, n$. In the paper, $\hat{\sigma}_{t,i}$ is estimated as the three-year rolling standard deviation of monthly excess returns, however, this value can be estimated using alternative criteria. The variable k_t can be stipulated in several ways. For an unlevered portfolio the variable is defined as

$$k_t = \frac{1}{\sum_i \hat{\sigma}_{t,i}^{-1}}\ , \tag{2.5}$$

Which results in the following formula for the weight of each asset *i* at time *t*

$$w_{t,i} = \frac{\hat{\sigma}_{t,i}^{-1}}{\sum_i \hat{\sigma}_{t,i}^{-1}}, \tag{2.6}$$

The levered RP portfolio is constructed by setting k_t equal to a constant value over time for all periods:

$$k_t = k$$

Resulting in the formula

$$w_{t,i} = k\hat{\sigma}_{t,i}^{-1}, \tag{2.7}$$

which ensures that each asset class targets a specified level of volatility each period. This constant level of volatility is achieved by altering the leverage of each position each month. Finally, the RP portfolio is constructed and rebalanced each month, where the monthly excess return is calculated as

$$r_t^{RP} = \sum_i w_{t-1,i}(r_{t,i} - rf_t)$$

By applying the methods and formulae presented above on realized returns for U.S stocks and bonds over the period 1926-2010, Asness et al. (2012) find interesting results shown in Figure 2.3.

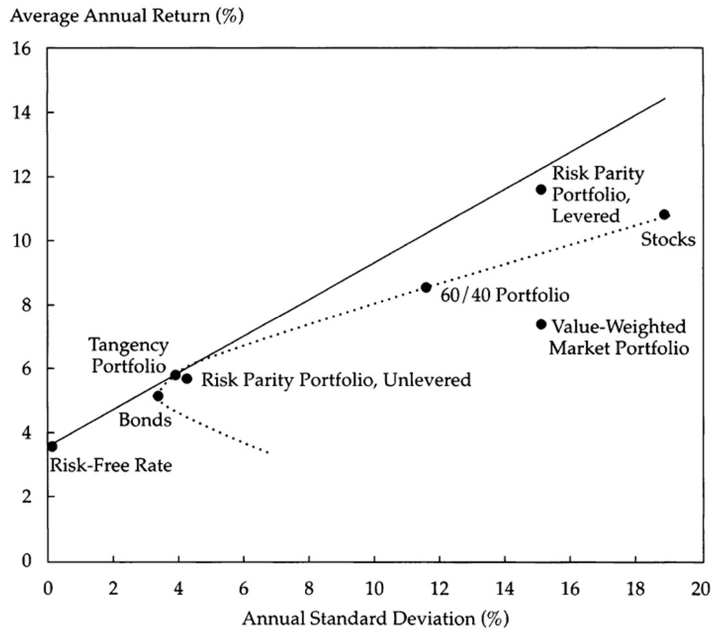


Figure 2.3 Efficient Frontier of portfolios of U.S stocks and Bonds used in the authors long sample over the period 1926-2010
Source: Asness et al. (2012)

Figure 2.3 displays the hyperbola representing all possible combinations of stocks and bonds over the entire period. As explained in Section 2.1, the addition of the risk-free T-bill rate in combination with portfolio of risky assets creates the efficient frontier of all assets. Contrary to what the CAPM theory would suggest, the diagram clearly shows that the risk-return characteristics of the value-weighted market portfolio are very different from the tangency portfolio. Asness et al. (2012) argue that there are two reasons causing this empirical observation. First, they argue that the market weights of stocks relative to bonds have changed over time in a manner that has caused the market portfolio to be located inside the hyperbola. Second, stocks receive a far higher weight allocation in the market portfolio relative to bonds, than what history has shown to be optimal. The authors highlight that since bonds have historically realized a higher SR and lower volatility than stocks, it makes sense that the tangency portfolio allocates a large portion of its weights to bonds. The unlevered risk parity portfolio, which is rebalanced on a monthly basis, possesses risk-return characteristics that closely resemble the tangency portfolio, displaying a slightly lower return and marginally higher volatility. This is precisely because the way that the RP portfolio is constructed, allocating weights based on the inverse of each asset's volatility, bonds make up a large portion of the portfolio.

Figure 2.3 also shows the performance of the levered risk parity portfolio, which displays the same volatility as the value-weighted market portfolio (by construction) but exhibits a far superior average annualized realized return. Therefore, the levered RP portfolio possesses a higher SR than the market portfolio. Furthermore, it also outperforms the 60/40 portfolio in terms of risk-adjusted returns. While it seems clear that investors should prefer a levered RP portfolio to the market portfolio Asness et al. (2012) propose a theory of leverage aversion to reconcile the discrepancy with the CAPM. They argue that an investor seeking a higher return than the tangency portfolio offers may be prepared to undertake more risk but be unwilling or unable to make use of leverage. This intuitively means that he will invest more wealth into stocks to increase returns. The authors posit that this alters the conclusion of the CAPM, which assumes that all investors invest on the efficient frontier of all assets. Therefore, in the presence of leverage averse investors, the market portfolio is not the equivalent of the tangency portfolio.

To test the performance of the RP portfolio's, Asness et al. (2012) perform a variety of time-series regressions. Two datasets are used. A *long* sample consisting of U.S stocks and bonds ranging between 1926-2010, and a *broad* sample which encompasses data on global stocks, U.S bonds, credit and commodities from 1973 to 2010. Two long-short portfolio are created. One goes long the RP portfolio and short the market portfolio. The other is also long the RP portfolio but short the 60/40 portfolio. The regressions that are conducted reveal positive and significant alphas for the unlevered RP, the RP and both long-short portfolios against the value-weighted market portfolio. All portfolios also report positive and statistically significant excess returns.

Testing U.S stocks, Black, Jensen, and Scholes (1972) find evidence indicating that the empirical SML is flatter than what the theoretical CAPM would suggest. Frazzini and Pedersen (2014) corroborate these findings using 40 years of out-of-sample findings in all other major asset classes. Whereas these studies focus on stocks, Asness et al. (2012) find the empirical SML to be too flat when testing across asset classes as shown in Figure 2.4. These results are obtained by regressing the excess returns of the *broad* sample, mentioned above, onto the value-weighted market portfolio. The betas of this time-series regression represent the slopes of each asset class relative to the market portfolio. The empirical SML is then constructed by conducting a cross-sectional regression of the average excess returns onto the realized betas and imposing a best fit line. This line represents the empirical SML. The authors assert that the flatness of the SML underpins the advantage of investing in safer assets.

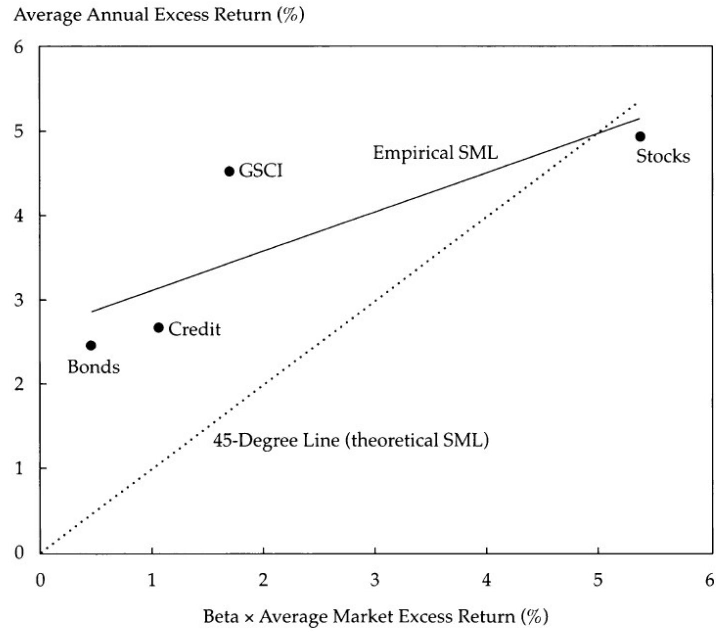


Figure 2.4 Security Market Line across asset classes used in the authors broad sample over the period 1973-2010.
Source: Asness et al.

The insights provided by the empirical study conducted by Asness et al. (2012) will play a central role in the methodology of the forthcoming analysis, in terms of asset allocation principles. This will be elaborated on in Chapter 4 of the paper, where the methodology will be presented. As well as contributing to the asset allocation decision, the risk parity approach to asset allocation is also present in some of the key literature that the paper will draw on with respect to time series momentum, a subject which the paper will now place its focus.

2.3 TIME SERIES MOMENTUM

Using data consisting of 24 commodity futures, 9 developed equity index futures, 13 developed government bond futures and 12 cross-currency forwards from January 1965 to December 2009 Moskowitz et al. (2012) conduct an in depth analysis of time-series momentum. A methodology for constructing time-series momentum factors is developed and evidence is found that their time-series momentum strategy produces abnormal excess returns. The paper will now present the theory and methodology used by Moskowitz et al. (2012) which will play a central role in the analysis performed in this paper.

Before describing how the TSMOM factor is calculated it makes sense to present how the ex-ante volatility is estimated and how lookback and holding periods are chosen. The ex-ante variance is estimated using exponentially weighted lagged squared daily returns:

$$\sigma_t^2 = 261\sum_{i=0}^{\infty}(1-\delta)\delta^i(r_{t-1-i}-\overline{r_t})^2 \ , \tag{2.8}$$

where the variance is annualized by the scalar 261. The component $(1-\delta)\delta^i$ are weights that sum to one and δ is set to make the centre of mass of the weights 60 days. Finally, $\overline{r_t}$ is the exponentially weighted average return. The standard deviation is then obtained by simply taking the square root of the variance. The authors highlight that other, more sophisticated volatility models can be used that also produce robust results. However, the lack of lookahead bias in this model is desirable. To further ensure that no lookahead bias contaminates the results, volatility estimates at time *t*-1 are applied to returns at time *t.*

To predict price continuation and reversal, the authors perform two pooled panel autoregressions on the data. Since the results of these regressions are very similar, this paper reports only one of these regressions. This regression takes the form:

$$r_t^s/\sigma_{t-1}^s = \alpha + \beta_h\, r_{t-h}^s/\sigma_{t-h-1}^s + \varepsilon_t^s \tag{2.9}$$

All excess returns are divided by their ex-ante volatility to place them on the same scale. The scaled excess return r_t^s/σ_{t-1}^s for instrument *s* in month *t* is then regressed on its counterpart lagged *h* months. All futures contracts and dates are stacked and the pooled panel autoregression is performed where *t*-statistics that account for group-wise clustering by time are calculated. The regression is conducted using lags of $h = 1,2,\dots,60$ months. Positive *t*-statistics are found for the first 12 months displaying significant return continuation in the data. At longer horizons, negative *t*-statistics are present, suggesting the presence of reversals.

Moskowitz et al. (2012) then investigate the profitability of different time-series momentum trading strategies. Here the lookback period *k*, i.e. the number of months that returns are lagged to determine the momentum signal, is changed for each strategy. Lookback periods of 1, 3, 6, 9, 12, 24, 36 and 48 months are tested. Moreover, the holding period *h,* i.e. the number of month that the position is held before rebalancing, is varied using the same time intervals as the lookback period. For each lookback period, every holding period is tested. The position size in each instrument is set to the inverse of its ex-ante volatility, each month. A single time series of monthly returns for each momentum strategy (*k,h*) is derived. This is obtained by calculating the average return of all *h,* currently active portfolios. The mean of all returns across all instruments is taken to create the time-series momentum strategy returns $r_t^{TSMOM(k,h)}$. To test for abnormal returns, defined in Section 2.1 as α, the authors run the following regression:

$$r_t^{TSMOM(k,h)} = \alpha + \beta_1 MKT_t + \beta_2 BOND_t + \beta_3 GSCI_t + sSMB_t + hHML_t + mUMD_t + \varepsilon_t \tag{2.10}$$

Where the term MKT represents the stock market and is proxied by the excess return on the MSCI World Index. The bond market BOND is proxied by the Barclays Aggregate Bond Index. The commodity market denoted GSCI is proxied by the S&P GSCI Index. Finally, the Fama-French factors for size, value and cross-sectional momentum are denoted SMB, HML and UMD, respectively. The authors report the *t*-statistics for the alphas of each regression. The *t*-statistics lead the authors to conclude that the optimal lookback horizon is 12 months paired with a holding period of 1 month. The *t*-statistic of the alpha obtained by this (k,h) strategy is reported as 6.61 for all assets.

Having established how the volatility is estimated and what the optimal lookback horizon and holding period were found to be, the paper will now progress to describe how the authors construct TSMOM factors. The formula for the TSMOM return of an instrument at time $t + 1$ is:

$$r_{t,t+1}^{TSMOM,s} = sign\left(r_{t-12,t}^{s}\right)\frac{40\%}{\sigma_t^s}r_{t,t+1}^{s} \tag{2.11}$$

The component $sign\left(r_{t-12,t}^{s}\right)$ will be either 1 or -1. The determination of the sign is based on the arithmetic mean of the past 12 months of returns. If the mean is positive (negative), $sign\left(r_{t-12,t}^{s}\right)$ will be equal to 1 (-1). It is this component that determines whether the position in this particular asset, *s* in current month, *t* will be long or short. The construction of the TSMOM factors draws on the risk parity approach to portfolio formation presented in the previous subsection. Specifically, the factors are created by allocating an equal amount of ex-ante volatility to each asset class. The $40\%/\sigma_t^s$ part of the formula represents this position size and is analogous to Equation 2.7 where $k_t = k = 40\%$. Furthermore, the constant value of *k* at 40% means that leverage is likely used. The authors scale the volatility to 40% because this results in a portfolio volatility of around 12% making it comparable to similar studies in the literature. In line with risk parity theory, the monthly TSMOM factors are created by simply taking the arithmetic mean of all the individual instruments TSMOM returns as follows:

$$r_{t,t+1}^{TSMOM} = \frac{1}{S_t}\sum_{s=1}^{S_t} sign\left(r_{t-12,t}^{s}\right)\frac{40\%}{\sigma_t^s}r_{t,t+1}^{s} \tag{2.12}$$

The TSMOM return is calculated for each of the 58 instruments in all available months between January 1985 and December 2009. All 58 futures contracts display positive predictability from the past 12-months of returns. Every contract realizes positive time-series momentum returns. Of these, 52 are statistically different from zero measured at the 5% significance level. The authors perform a regression to test whether the TSMOM strategy produces additional returns beyond those achievable from a long only strategy. Here the TSMOM returns are regressed onto returns calculated using Equation 2.2 where $sign\left(r_{t-12,t}^{s}\right)$ is set to 1 at all times. This regression produces positive alphas in 90% of the cases, with 26% of the alphas displaying statistical significance. Hereby, the authors show that the application of the TSMOM strategy does indeed provide additional returns greater than those of the long only risk parity strategy. An identical regression as the one shown in Equation 2.1 is performed using the diversified TSMOM returns calculated in Equation 2.12. The results of this regression show that the TSMOM strategy produces a significant alpha of approximately 1.58% per month. Again, the authors test the performance of the TSMOM strategy against its long-only counterpart and display the superiority of the former in a cumulative excess returns plot shown in Figure 2.5.

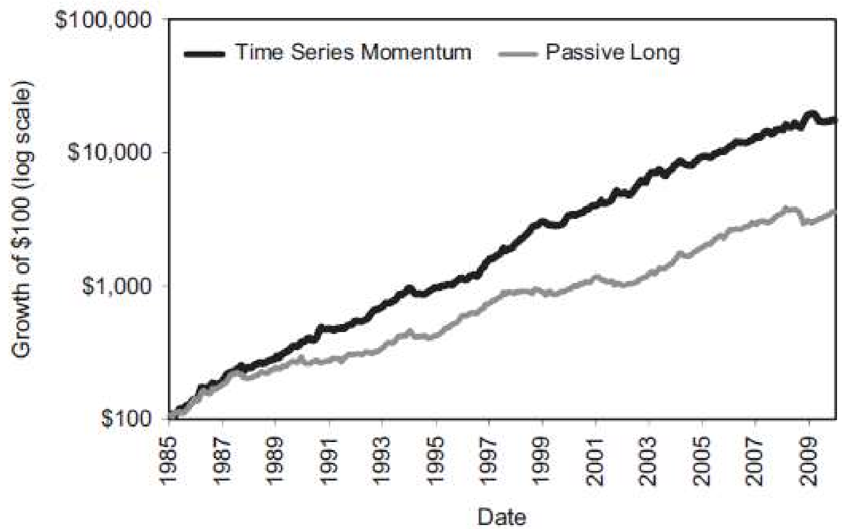


Figure 2.5 Cumulative excess return of the time series momentum and diversified passive long strategy over the period January 1985 to December 2009 used by the authors
Source: Moskowitz et al. (2012)

Moskowitz et al. (2012) highlight the impressive performance of the strategy during the global financial crisis (GFC), emphasizing the large TSMOM profits in the last quarter of 2008, where the GFC was at its peak. They attribute this to the TSMOM strategy's tendency to perform well during extreme markets. However, the strategy endures large losses in the event of sharp trend reversals as it fails to adjust its positions in time.

Moskowitz et al. (2012) conduct a great deal of tests beyond those presented above. Though interesting, these tests are not of direct relevance to the paper and will therefore be exempt from elaboration. Rather, the paper will now present its own unique addition to the TSMOM theory.

2.4 THIS PAPER'S CONTRIBUTION TO THE TSMOM THEORY

2.4.1 Long Only TSMOM

A number of studies find evidence that the majority of the returns associated with long/short momentum strategies is attributable to the short position in losers as opposed to the long position in winners. For instance, measured in absulte value, Jegadeesh & Titman (2001) uncover that abnormal returns are more prominent in loser portfolios than in winners. Specifically, they find that the alphas of winners portfolios are 0.46 and 0.50 measured against the CAPM and Fama-French three-factor model, respectively. The losers portfolio displays an alpha of -0.79 against the CAPM and -0.85 measured against the Fama-French factors. Obviously, when shorting the losers portfolio, these returns are positive. Hong, Lim, and Stein, (2000) test cross-sectional momentum profits on portoflios divided into deciles according to size, from the smallest in decile 1 to the largest in decile 10. Within each decile, three portfolios are formed – P1 which is an equally weighted portfolio of the worst-performing 30 percent of stocks, P2 consists of the middle 40 percent and P3 comprises the best-performing 30 percent. Implementing the formula $(P2 - P1)/(P3 - P1)$ the authors find that for all size deciles but the first, the middle minus losers account for between 73 and 100% of the excess return. This indicates that the short positions in losers are the driving factor in cross-sectional momentum returns. Lastly, in a paper that examines the profitability of momentum strategies, Lesmond et al. (2004) find that up to 70% of momentum profits on long/short portfolios arise from the short positions. The authors find that these positions are precisely the ones that would have the highest trading costs associated with them. They argue that the disproportionately high trading costs associated with short selling these past losers would completely eliminate the profits generated by the strategy. Given this criticism, it is of interest to conduct a dedicated analysis of long-only TSMOM strategies and determine whether they produces attractive performance metrics.

Moskowitz et al. (2012) specify that $sign(r^s_{t-12,t})$ takes either the value 1 or -1, depending on whether the arithmetic mean of the past twelve months of returns are positive or negative, respectively. A simple alteration of this specification enables the formula presented by the authors to be implementable as a long only portfolio. Specifically, if the past k months of returns have a negative mean, $sign(r^s_{t-k,t})$ will take the value of 0, if positive, it will take the value of 1 as before. This simply means that instead of shorting assets with negative momentum, we simply remove them from the portfolio at that time, investing zero wealth in them. While this solves the problem of how to impose a long-only constraint on the portfolio, a new question arises – how is the wealth accumulated from the complete sale of an asset allocated?

In practice there are many possible avenues to take in the event of an asset having a $sign(r^s_{t-k,t})$ value equal to zero. In this case the paper will assume that the wealth previously invested in an asset that must now be excluded, can be allocated to assets that have been leveraged, thereby reducing financing costs. If the portfolio is not using external financing to leverage its positions, the portion of wealth can be invested at the risk-free rate.

2.4.2 The Levered and Unlevered TSMOM Factors with Costs

One of the focal points of this paper is to ascertain the extent to which it is possible for an individual investor to implement a time-series momentum strategy and realize superior portfolio performance compared to other asset allocation strategies. To this end, the paper will extend the formula for TSMOM returns derived by Moskowitz et al. (2012). The extension will consist of two components that are of importance when transitioning from a paper portfolio to a real-life portfolio. These are transaction costs and financing costs. Furthermore, the paper develops a TSMOM strategy that does not use leverage. First the paper will present the new levered TSMOM (LTSMOM) formula and explain the changes that have been made. Following this, the unlevered TSMOM (UTSMOM) formula will be shown. After having presented the two new formulas, the paper will provide a detailed account of how transaction and financing costs will be calculated.

The Levered TSMOM Factor

The LTSMOM factor is calculated using the following formula:

$$r^{LTSMOM}_{t,t+1} = \frac{1}{S_t}\sum_{s=1}^{S_t}\left(sign\left(r^s_{t-k,t}\right)\frac{30\%}{\sigma^s_t}r^s_{t,t+1}\right) - TC_{t+1} - FC_{t+1}, \tag{2.13}$$

Here TC^s_{t+1} denotes the transaction costs associated with the sale and purchase of assets in the portfolio at time $t+1$. FC_{t+1} represents the potential financing costs incurred due to the possible use of leverage in the portfolio. This size of FC_{t+1} is calculated at the portfolio level and has a minimum value of 0. As explained above, since this is a long only strategy, the value of $sign(r^s_{t-k,t})$ is either 0 or 1.

Finally the assets are scaled to have volatilities of 30% as opposed to the 40% used by Moskowitz et al. (2012). The reason for this alteration finds it roots in the theory presented in Section 2.3. Moskowitz et al. (2012) explain that by scaling the volatilities of each asset to 40%, the overall portfolio volatility becomes approximately 12% per year. However, the data in their study consists of 58 assets spread across four asset classes. Intuitively, this creates a more diversified portfolio than is possible using 21 assets spread across two asset classes. The theory presented in Section 2.1 and Section 2.2.1 would suggest that this higher degree of diversification likely influences the correlation structure of the portfolio, facilitating a lower overall portfolio volatility. Against this background, preliminary tests have been conducted that displayed portfolio volatilities of around 17% when scaling each asset to have a volatility of 40%. However, reducing the scaling to 30%, the desired volatility of around 12% is obtained. These tests are not reported in this paper, but the resulting portfolio volatilities are observable in the results. The reason for targeting a portfolio variance of 12% is to make the results easily comparable to other portfolios in the literature.

The Unlevered TSMOM Factor

The UTSMOM factor is calculated using the following formula

$$r_{t,t+1}^{UTSMOM} = \sum_{s=1}^{S_t}\left(sign\left(r_{t-h,t}^{s}\right)\frac{\sigma_{t,s}^{-1}}{\sum_s \sigma_{t,s}^{-1}} r_{t,t+1}^{s}\right) - TC_{t+1}\ , \tag{2.14}$$

Two changes are made to Equation 2.13 to arrive at the UTSMOM factor shown in Equation 2.14. First, the $\frac{30\%}{\sigma_t^s}$ component is replaced by Equation 2.6, namely $\frac{\sigma_{t,s}^{-1}}{\sum_i \sigma_{t,s}^{-1}}$. As explained in Section 2.3 this is a form of risk parity asset allocation whereby assets with lower volatilities receive higher portfolio weights. Since the assets are not volatility scaled, the resulting portfolio will, according to the theory presented in Section 2.2.1, have a low volatility, resembling the minimum-variance portfolio. The second change is the removal of the FC_{t+1} component. This term is removed since the strategy does not use leverage and is therefore not subject to financing costs. As with the levered portfolio, it is crucial to understand the mechanics of what happens when $sign\left(r_{t-h,t}^{s}\right)$ is equal to 0. This decision is essentially up to the investor. This paper will determine weights before accounting for the value of $sign\left(r_{t-h,t}^{s}\right)$. This means that when one ore more assets have $sign\left(r_{t-h,t}^{s}\right)$ equal to zero, the portfolio weights will not sum to one. In this event, the paper assumes that the portion of portfolio wealth that is not allocated to assets is instead invested at the risk-free rate, producing an excess return of zero. An alternative approach could be to calculate portfolio weights, integrating $sign\left(r_{t-h,t}^{s}\right)$ into the calculation. This would create the formula

$$r_{t,t+1}^{TSMOM} = \sum_{s=1}^{S_t}\left(sign\left(r_{t-h,t}^{s}\right)\frac{\sigma_{t,s}^{-1}}{\sum_s sign\left(r_{t-h,t}^{s}\right)\sigma_{t,s}^{-1}} r_{t,t+1}^{s}\right) - TC_{t+1}\ , \tag{2.15}$$

which is a perfectly feasible method to use. However, there is a significant downside to this approach. Imagine an extreme scenario where all assets but one have $sign\left(r_{t-h,t}^{s}\right)$ equal to zero. This would result in all wealth being allocated to one single asset. As was discussed in Section 2.1, diversification produces great benefits in terms of reducing the risk of the portfolio. Should the investor find himself in the described scenario, which would likely be due to significant market turbulence, with almost all assets having negative mean returns over the lookback horizon *k*. In such a situation it seems rather unwise to allocate 100% of your wealth to a single asset, which would be the case in this example. For this reason, the paper uses the approach described in Equation 2.14. In the hypothetical example presented, a great deal of wealth would be allocated to the risk-free asset. Since the UTSMOM strategy is more suited to an investor with a high degree of risk aversion, this approach seems more appropriate.

Having presented the new LTSMOM and UTSMOM strategies, the paper will now turn its attention to the transaction and financing costs embedded within them. Drawing on relevant theory, the paper will begin by explaining the relevance of transaction costs to the implementation of the time series momentum strategy. Moreover, derives a formula to account for the proportional transaction costs associated with the calculation of strategy returns. Following this, the paper will address the issue of financing costs that would be inherent in the real-life implementation of the LTSMOM strategy. Here, the paper derives a formula that adjusts the LTSMOM returns to account for these financing costs.

2.4.3 Transaction Costs

Transaction costs have been the subject of much debate in terms of the application of momentum strategies in the real world. Korajczyk and Sadka (2004) find that some equal weighted strategies perform poorly given transaction costs whereas value-weighted and liquidity-weighted strategies still provide desirable results. Lesmond et al. (2004), however, find that all of the strategies they test are useless when transaction costs are accounted for. Frazzini et al. (2015) and Asness et al. (2013), on the other hand find evidence that momentum strategies are implementable and do supply abnormal excess returns. While the conclusions drawn from the scholars differ, some areas of attention remain the same. Common for each of these investigations is the acknowledgement that proportional costs are not the dominating factor in reducing after-cost excess returns. Rather non-proportional costs created by the price impact caused by large institutional investors account for the majority of the transaction costs. Since this paper is focused on the applicability of a momentum strategy from an individual investor's perspective, price impact is arguably not a concern. For this reason, the paper will ignore nonproportional transaction costs associated with price impact.

Although the reviewed literature finds proportional costs to cause little damage to the excess returns of momentum strategies used by institutional traders, this may not be the case for individual investors. Institutional investors likely have much lower proportional costs compared to individuals who are restricted to using online commercial platforms or other costly avenues for trading. Proportional costs typically refer to the difference between the buy and sell price on an asset, its bid-ask spread. Broker costs are also considered a proportional cost.

$$TC_{t+1} = \sum_{s=1}^{S} \left(|w_{t+1}^s - w_{t+}^s| * (BC + BA_{t+1}^s) \right) \quad , \tag{2.16}$$

where BC is a given percentage rate a broker charges to execute a transaction and will be fixed for the entire sample period. BA_{t+1}^s is the percentage cost incurred due to the bid-ask half-spread and varies over time and across assets. The desired weight of each asset *s* at time *t* + 1 is given by w_{t+1}^s and the current weight before rebalancing is represented by w_{t+}^s. These parameters are different for the levered and unlevered strategies. The reason for this is that the levered portfolio allocates weights to each asset solely based on its own volatility and the portfolio weights may sum to more than one. Conversely, asset weight allocations in the UTSMOM portfolio are dependent on the weight allocated to the other assets. The weight parameters for the LTSMOM strategy are given by the following expressions:

$$w_{t+1}^s = \frac{1}{S_{t+1}} sign\left(r_{t-k-1,t+1}^s\right) \frac{30\%}{\sigma_{t+1}^s} \quad , \tag{2.17}$$

$$w_{t+}^s = \frac{1}{S_t}\, sign\left(r_{t-k,t}^s\right)\left(1 + r_{t,t+1}^s\right) \frac{30\%}{\sigma_t^s} \tag{2.18}$$

The weight parameters for the Levered Risk Parity (LRP) strategy, which will be elaborated on in Section 4.2, are calculated almost identically, with the difference being that $sign\left(r_{t-k,t}^s\right)$ is equal to 1 at all times.

For the UTSMOM portfolio the weights are calculated as follows:

$$w_{t+1}^s = sign\left(r_{t-k-1,t+1}^s\right) \frac{\sigma_{t+1,s}^{-1}}{\sum_s \sigma_{t+1,s}^{-1}} \quad , \tag{2.19}$$

$$w_{t+}^s = sign\left(r_{t-k,t}^s\right) \frac{\left(1 + r_{t,t+1}^s\right) \frac{\sigma_{t,s}^{-1}}{\sum_s \sigma_{t,s}^{-1}}}{\sum_{s=1}^{S}\left(1 + sign\left(r_{t-k,t}^s\right) r_{t,t+1}^s\right) \frac{\sigma_{t,s}^{-1}}{\sum_s \sigma_{t,s}^{-1}}} \tag{2.20}$$

As defined above, the portion of portfolio wealth that is not allocated to assets due to $sign\left(r_{t-k,t}^s\right)$ being equal to zero is instead invested at the risk-free rate. Therefore, this wealth remains constant over the period, neither growing nor declining. The $sign\left(r_{t-k,t}^s\right)$ component in the denominator of Equation 2.20 accounts for this constant level of wealth when relevant. Again, the weights for the unlevered risk parity (URP) strategy are identical except for the constant value of 1 for $sign\left(r_{t-k,t}^s\right)$. The paper will now progress to explain how financing costs are calculated.

2.4.4 Financing Costs

Asness et al. (2012) present a convincing argument advocating the use of leverage on portfolios that are heavily concentrated in safe assets, exploiting the flatness of the SML to realize abnormal returns. However, the authors emphasize that some investors may be unable or unwilling to use leverage in practice. Certainly, from the perspective of an individual investor, it is within reason to assume that the interest rate on borrowing will be higher than the interest rate that can be realized by investing in a risk-free instrument. A higher borrowing rate results in a lower return per unit of standard deviation than the CML would suggest. The Sharpe ratio is thus reduced, meaning that the investor will receive a lower risk-adjusted return.

To capture this effect in the LTSMOM returns the derivation of FC distinguishes between the borrowing and lending rate:

$$FC = \max(r^{PB}L, 0)\,, \tag{2.21}$$

where

$$L = \frac{1}{S_t}\sum_{s=1}^{S}\left(sign\left(r_{t-k,t}^{s}\right)\frac{30\%}{\sigma_t^s} - 1\right) \tag{2.22}$$

The formula equates the potential cost from borrowing at the portfolio level. The term L determines the overall portfolio leverage at time *t*. FC will take on one of two forms depending on the value of L:

1. $L > 0 : FC = r^{PB}L$
2. $L \leq 0 : FC = 0$

In case 1, the portfolio is levered and must therefore pay the financing costs associated with funding the leverage. The rate used is r^{PB}, which will vary depending on the loan broker. Some brokers offer a rate comprised of two parts – the variable risk-free rate and a fixed annual premium (Interactive Brokers, 2019a). As mentioned in Section 2.3, the method prescribed by Moskowitz et al. (2012) uses excess returns in its calculations as does the method used in this paper. For this reason, r^{PB} must only consist of the fixed premium and not the risk-free rate, otherwise the LTSMOM returns would be penalized twice with the risk-free rate.

In case 2, the portfolio is unlevered at time *t*. Therefore, there is no external funding and no cost must be enforced. For $L < 0$ a portion of the investors wealth is invested in the risk-free rate. However, as with case 1, since LTSMOM returns are net of the risk-free rate the excess return of this investment is 0. Hence, no additional return is added. An important characteristic of Equation 2.22 is that inactive assets will contribute the value -1 to the summation of leverage. What this means is that the wealth that would have been allocated to the asset in an active state will instead be used to lever up the active positions. This means that it is possible for the LTSMOM strategy to experience states where it is in fact not levered. This characteristic serves to tame the amount of leverage used in the portfolio which has several benefits from at practical point of view. Firstly, applying leverage using external financing can be costly for an individual investor, which may prove suboptimal. Secondly, while applying leverage enables an investor to realize larger gains than otherwise possible, it simultaneously exposes the investor to significant losses, which may eventually prove to be too large for the investor to bare. Thirdly, given that the borrowing rate is likely higher than the risk-free rate it makes little sense to invest money in the risk-free rate while borrowing at a higher rate. Hence, using all the wealth available to the investor prior to drawing on external financing seems like a more appropriate approach to the implementation of the strategy.

3 DATA

This section of the paper explains relevant details regarding the data used in the analysis. Section 3.1 describes where data has been collected and what considerations have been made when choosing this data. The paper conducts preliminary data preparation in Section 3.2, which primes the data for analysis.

3.1 DATA COLLECTION AND CONSIDERATIONS

3.1.1 ETFs and the Risk-free Rate

The assets that have been selected for the analysis consist of the exchange traded funds (ETF) listed in Table 3.1. The ETF data is comprised of 15 developed equity index funds and 6 bond index funds, summing to a total of 21 ETFs. The paper collects daily high and low prices, close prices, adjusted close prices, and trading volumes from the S&P Capital IQ Database. Annual expense ratios are retrieved from the iShares website (IShares, 2019). The paper collects data on the 1-month Treasury Bill rate from the S&P Capital IQ Database. All data covers the period from January 2004 to November 2019. As will be explained in more depth in the following sections, daily high and low prices are used to estimate the bid-ask spread. Adjusted close prices are used to calculate returns and volatilities. The 1-month Treasury Bill is chosen as the risk-free rate and used to calculate excess returns. Expense ratios are used to calculate ETF specific excess returns. Trading volume data is used mainly as a sanity check on the data to ensure that the assets being analysed are traded at such a level that render them liquid enough to implement the time-series momentum strategy.

Table 3.1

Descriptive statistics of the ETFs used in the analysis.

Ticker	Asset Name	Inception Date	Average Daily Volume ($m)	Annual Expense Ratio
IVV	iShares Core S&P 500 ETF	5/19/2000	$1,248.2	0.04%
IWM	iShares Russell 2000 ETF	5/26/2000	$3,228.6	0.19%
EWA	iShares MSCI Australia ETF	3/18/1996	$52.4	0.47%
EWC	iShares MSCI Canada ETF	3/18/1996	$65.1	0.47%
EWQ	iShares MSCI France ETF	3/18/1996	$35.4	0.47%
EWG	iShares MSCI Germany ETF	3/18/1996	$99.7	0.47%
EWH	iShares MSCI Hong Kong ETF	3/18/1996	$128.1	0.48%
EWI	iShares MSCI Italy ETF	3/18/1996	$22.9	0.47%
EWJ	iShares MSCI Japan ETF	3/18/1996	$446.8	0.47%
EWN	iShares MSCI Netherlands ETF	3/18/1996	$7.8	0.47%
EWS	iShares MSCI Singapore ETF	3/18/1996	$15.9	0.47%
EWP	iShares MSCI Spain ETF	3/18/1996	$27.8	0.47%
EWD	iShares MSCI Sweden ETF	3/18/1996	$12.6	0.53%
EWL	iShares MSCI Switzerland ETF	3/18/1996	$39.8	0.47%
EWU	iShares MSCI United Kingdom ETF	3/18/1996	$79.4	0.47%
AGG	iShares Core U.S. Aggregate Bond ETF	9/26/2003	$505.9	0.05%
LQD	iShares iBoxx $ Investment Grade Corporate Bond ETF	7/26/2002	$1,196.7	0.15%
IEF	iShares 7-10 Year Treasury Bond ETF	7/26/2002	$539.4	0.15%
TLT	iShares 20+ Year Treasury Bond ETF	7/26/2002	$1,279.5	0.15%
SHY	iShares 1-3 Year Treasury Bond ETF	7/26/2002	$262.6	0.15%
TIP	iShares TIPS Bond ETF	12/5/2003	$152.7	0.19%

Note: Daily volume in dollars is calculated by multiplying the daily close price with the volume traded that day. The average is taken over the period 1/11/2018 – 31/10/2019. Expense ratios are obtained from the iShares website, as are the inception dates.

The decision to select ETF's as the assets of interest has been given much consideration. ETFs are relatively simple to trade with most online trading platforms providing easy access to the instruments. As shown in Figure 3.1, the average daily trading volumes of the selected ETFs increased significantly up to around 2007, where they have averaged roughly 4.75 million shares a day between January 2007 and November 2019. Over the most recent year of data, between November 2018 and October 2019 the paper calculates that the average daily trading size has been almost $450 million. To put this into perspective, over the same period this paper calculates that Goldman Sachs traded and average of approximately $584 million a day, General Motors traded $344 million a day and IBM traded $563 million a day. All these stocks are part of the S&P 500 and it is therefore within reason to presume that they are fairly liquid. The ETF with the lowest trading volume in the sample is the iShares MSCI Netherlands ETF, having traded $7.8 million dollars a day on average over the period. This is, of course, much lower than the stocks mentioned and a great deal less than the sample average. However, for the purposes of this investigation, the trading volume should provide adequate liquidity.

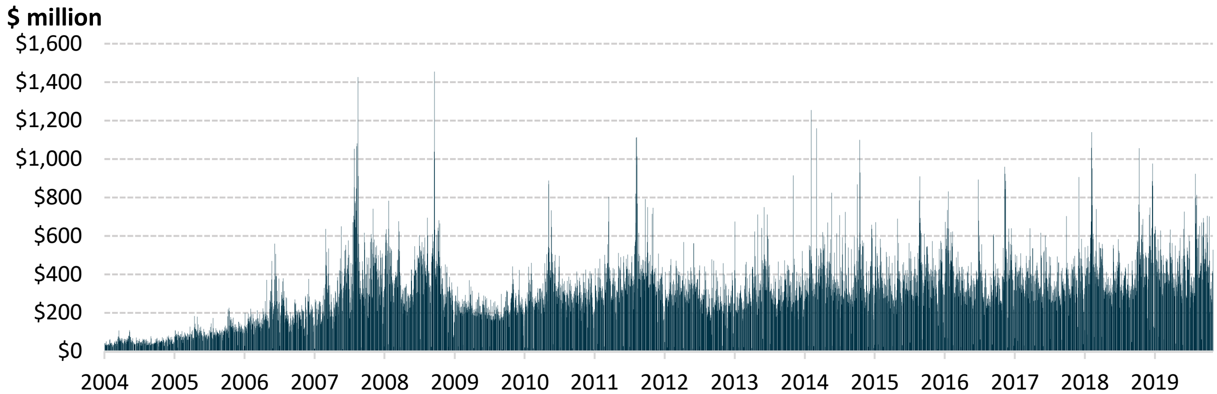


Figure 3.1 Average trading volume in USD of all ETFs in the data over the period January 2004 to October 2019

Drawing on the theory presented in Section 2.1, it can be argued that a single ETF possesses a great deal of diversification with respect to the idiosyncratic risk associated with the underlying assets that compile the ETF. Therefore, firm specific risk is diversified away, leaving only systematic risk. By creating a portfolio of 15 different index ETF's representing 14 countries, the portfolio also diversifies some of the country-specific risk away. Moreover, including 6 bond ETFs in the portfolio facilitates some asset class diversification as well.

3.1.2 Broker and Financing Costs

The paper determines the broker commission applicable when entering a transaction with an ETF and the financing cost of using leverage based on observable public prices on a range of online broker sites. While these prices may vary considerably across brokers, it seems within reason to apply the costs from the broker offering rates most suited to the type of trading that characterizes the LTSMOM and UTSMOM strategies the best, while still maintaining a realistic approach to the analysis. Given that the portfolios are rebalanced on a monthly basis, a TSMOM trader should seek to obtain as low a trading costs as possible. However, since the LTSMOM strategy uses leverage, keeping financing costs to a minimum is also desirable. Therefore, finding a broker that offers low costs in both cases is optimal. Unfortunately, one broker may offer very cheap trading costs, but high financing costs and vice versa. Conducting extensive searches on the internet, it has not been possible to find a broker that both offers the lowest trading and financing costs simultaneously. Hence, the paper seeks a compromise which is found on the online trading platform *Interactive Brokers.* The paper does not assume that the trades in this paper would be implemented using this broker, but rather use the information as a point of departure to gain some bearings in terms of what an investor could expect to be charged in the real world.

The trading cost of almost all the instruments in the dataset is 0.1% of transaction size. A select few of the instruments offer a slightly lower rate. US ETFs are traded at a fixed price of USD 0.005 per share and USD 1.00 per order (Interactive Brokers, 2019b). For simplicity, the paper will use 0.1% of transaction size as the broker commission in the analysis. As will be explained in Section 4.2, a sensitivity analysis is conducted where the transaction costs are both higher and lower than 0.1% providing deeper insights into the effects of transaction costs.

The annualized financing cost quoted on InteractiveBrokers.com is given by the risk-free rate plus a premium of 2.5% (Interactive Brokers, 2019a). To arrive at the monthly rate this number is then divided by 12. This will be the rate that the paper uses as its benchmark financing cost in the forthcoming analysis. It must be noted that cheaper rates are obtainable if the trader is able to qualify for a PRO membership, where the rate decrease depending on investment size. As with the transaction costs, a sensitivity analysis using both a higher and lower financing cost will be conducted

3.2 PRELIMINARY DATA PREPARATION

This subsection of the paper will describe how initial data preparation procedures have been conducted. It will begin by describing how excess returns are calculated. Following this, the method for calculating ex-ante volatility used in the UTSMOM and LTSMOM formulas will be presented. Finally, lacking empirically observed bid-ask spread transaction costs, the paper will explain how these are estimated.

3.2.1 Calculating Excess Returns

To calculate the monthly return of the data, first the logarithm of all the adjusted close prices are taken:

$$\ln\left(S_{t,T}\right)$$

Taking the first differences of the logarithmic prices yields the monthly returns:

$$R_t^s = \Delta \ln(S_t) = \ln(S_t) - \ln(S_{t-1}) \tag{3.1}$$

Transforming the annualized 1-Month Treasury Bill rate to a monthly rate, by dividing it by 12, the excess return is then calculated by subtracting the monthly T-bill rate from the return at time *t.*

$$r_t^s = R_t^s - rf_t \tag{3.2}$$

Different perspectives exist concerning what the excess return means. One perspective is that the investor borrows at the risk-free rate and invests in an asset, meaning that the risk-free rate is an actual cost that is incurred. A second perspective is that the risk-free rate is the rate at which an investor could safely house his wealth and is therefore not an actual cost but rather an opportunity cost. This paper follows the second perspective.

3.2.2 Estimating Ex-ante Volatility

When calculating the weights in the LTSMOM and UTSMOM strategies, the standard deviation of each asset is the central component. To this end, ex ante volatilities must be estimated. This paper will follow the methodology of Moskowitz et al. (2012), using an exponentially weighted lagged squared daily returns model. The ex-ante variance is calculated using the formula:

$$\sigma_t^2 = 261 \sum_{i=0}^{\infty} (1-\delta)\delta^i (r_{t-1-i} - \bar{r}_t)^2 \tag{3.3}$$

The standard deviation is then calculated by simply taking the square root of the variance:

$$\sigma_t = \sqrt{\sigma_t^2} \tag{3.4}$$

In Equation 3.3 t is time measures in months, whereas i is measured in days. The scalar 261 annualizes the daily variance. Moskowitz et al. (2012) vary δ so that the centre of mass is 60 days. For simplicity this paper follows the methodology of Babu, Levine, Ooi, Pedersen, and Stamelos (2019) and sets the input δ to 0.98.

3.2.3 Modelling Spread Transaction Costs

Lesmond et al. (2004) and Korajczyk and Sadka (2004) acquire bid-ask spread data from the NYSE TAQ database, Frazzini et al. (2015) use unique live trading data on bid and ask quotes. Unfortunately, this paper has access to neither of these sources of data. Moreover, the availability and reliability of the data from the BLOOMBERG and Capital IQ (COMPUSTAT) databases for historical bid-ask data is underwhelming. Therefore bid-ask spreads must be estimated. While many methods are available to estimate transaction costs, each method possesses both strengths and weaknesses. When modelling the transaction costs used in the analysis, careful consideration has been taken to select the appropriate technique. One method which has been considered is derived by Roll (1984) and is captured by the expression: $Spread = 2\sqrt{-cov}$. However, an underlying premise for this method is that markets are efficient an autocovariances are therefore negative. Harris (1990) finds that many of the autocovariances are nonnegative resulting in undefined results. Given the lack of reliable bid-ask quotes and the flaws of the Roll estimate, the paper uses a different approach to estimate the spread. The paper will use the method prescribed by Corwin and Schultz (2012), drawing on daily high and low prices. The approach rests on the idea that the high-low price ratio of an asset consists of its true variance and the bid-ask spread. The authors argue that the variance component changes in proportion with time, whereas the bid-ask component does not. Hence, by deriving one equation which is a function of the high-low ratios over two consecutive days and another that is a function of the ratio from a single two-day period, it is possible to solve for the spread and variance components individually. By path of several derivational steps, which this paper will overt, the following spread estimate is constructed:

$$S = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}} \tag{3.5}$$

where,

$$\alpha = \frac{\sqrt{2\beta - \sqrt{\beta}}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} \quad ,$$

$$\gamma = \left[\ln\left(\frac{H^0_{t,t+1}}{L^0_{t,t+1}}\right)\right]^2 \quad ,$$

$$\beta = \sum_{j=0}^{1}\left[\ln\left(\frac{H^0_{t+j}}{L^0_{t+j}}\right)\right]^2$$

Here $H^0_{t,t+1}$ is the high price over the two days t and $t+1$, and $L^0_{t,t+1}$ is the low price over the same two days. H^0_{t+j} is the high price on day $t+j$ and L^0_{t+j} is the low price on the same day. Since the spread is the cost for a round-trip, that is the cost of buying and selling an asset, the spread estimate must be halved, to account for a one-way cost. Moreover, this paper will take the arithmetic mean of all daily half-spread estimates in a given month for each asset and use these as the bid-ask transaction costs resulting in the following formula:

$$BA^s_t = \frac{1}{D}\sum_{d=1}^{D}\frac{S^s_i}{2} \tag{3.6}$$

Where BA^s_t is the average bid-ask half spread in month t on asset s. D represents the total number of observations in the given month and will vary slightly from month to month. This estimate will be used to calculate transaction costs arising from the bid-ask spread. The reason for using an average spread estimate instead of the precise daily spread estimate on the execution day is simply to account for the fact that on a single day a trade cost may be unusually high or low than what is representative for the period of time. For instance, if the bid-ask spread is unusually high for some reason on a specific day, the trader would in a real-life situation perhaps wait a day before executing the trade. If the trader is in a period where the spread is high, this will still be represented in the results, contrarily is the spread on that day reveals itself as an outlier the trading cost will be reduced. It could be argued that this approach aligns better with reality than simply using the potentially extreme value on a specific day, since many traders use limits on the sale and purchase of assets.

4 METHODOLOGY

This section of the paper provides a comprehensive account of the methodology that is used in the analysis. Section 4.1 describes how the data is tested for the presence of price continuation. The paper presents the methodology that is used to test the performance of the LTSMOM and UTSMOM strategies in Section 4.2. The methods used to calculate the performance measures themselves are described in Section 4.3.

4.1 POOLED PANEL AUTOREGRESSION

Hurst et al. (2017) highlight that clear trends have been elusive in recent years. To this end, the paper will analyse the data to determine whether a trend exists. To assess the level and significance of price continuation in the data, the paper conducts a pooled panel regression on volatility scaled monthly excess returns data. The results of this analysis contribute to answering Question 1. The methodology in the following is adopted from Moskowitz et al. (2012).

The paper performs the pooled panel autoregression using the formula,

$$r_t^s/\sigma_{t-1}^s = \alpha + \beta_h r_{t-h}^s/\sigma_{t-h-1}^s + \varepsilon_t^s \tag{4.1}$$

where the ex-ante volatility scaled excess returns r_t^s/σ_{t-1}^s of asset s in month t are regressed onto its h month lagged counterpart $r_{t-h}^s/\sigma_{t-h-1}^s$. Moskowitz et al., (2012) use sixty lags in their pooled panel regression, applied to data ranging between 1965-2009. Sixty lags equate to 5 years of data. Since the regression is performed on almost 45 years of data, this lag length may be appropriate. The analysis in this paper uses only approximately 15 years of returns data. Therefore, sixty lags would arguably sacrifice too much data than what seems reasonable. For this reason, the paper uses 24 lags to predict price continuation and reversals. The paper stacks all volatility scaled excess returns and dates in a single dataset with each asset receiving an index number which is used to identify it the pooling process and runs the regression.

The paper only reports the t-statistics of this regression in the analysis. Whereas other metrics also contain information that contribute to explaining the data such as the adjusted R^2, these will be omitted. The reason for this is that much of the analysis focuses on analysing different lookback horizons that provide more insightful results relevant to the analysis of this paper. Due to space constraints, the paper judges that the omission of these values is appropriate.

The paper uses t-statistics that are computed using standard errors that are clustered by time. Positive (negative) t-statistics will be present for positive (negative) autocorrelation. Since the degrees of freedom are well in excess of 120, t-statistics are significant at the 5% level at an absolute value of 1.96 (Stock & Watson, 2015, p. 804). The t-statistics provide an indication of whether a trend exists, how long it lasts, and when it stops or even reverses.

4.2 The Time Series Momentum Strategy

As presented in Section 2.3 of the paper, Moskowitz et al. (2012) derive a formula for calculating the TSMOM strategy. A modification to this formula was then derived to account for no short selling, transaction costs, financing costs and the fact that fewer assets are under investigation in this paper than in the study performed by Moskowitz et al. (2012). The following subsection will describe how the paper investigates each of these elements.

First, the method used to determine optimal lookback horizons is developed. The purpose of this is to identify and select the portfolio with the best performance, with respect to lookback horizons, that will be used in later sections of the analysis. Moreover, it provides insights into the development of time-series momentum characteristics that will contribute to the extant literature. This method is used in the analysis of both the LTSMOM and UTSMOM strategies. Following this, the paper focuses on the levered strategies and explains the methodology that will be used in their analysis. Next, the paper presents the methodology that is used for analysing the unlevered strategies. Thereafter, the paper presents two standard investment strategies and explains how a comparison of all strategies will be performed. The section will conclude by presenting an account of how the performance metrics that are used throughout the analysis are calculated and what considerations have been made in their selection.

4.2.1 The Optimal Lookback Horizon

Moskowitz et al. (2012) identify twelve months as the most optimal lookback period for the TSMOM strategy. Since this paper tests a new asset class, in a different period, with financing and transaction costs and no short-selling, it cannot be taken for granted that the optimal lookback horizon is the same as any of the previous studies on time-series momentum. Therefore, the paper seeks to identify the optimal lookback horizon for this specific set of data. Furthermore, a method is used to test the effect that transaction costs and financing costs have on the optimal lookback horizon. This is achieved by changing the lookback value h in the component $sign(r_{t-h,t}^{s})$ of the LTSMOM and UTSMOM formulas. Specifically, the paper constructs LTSMOM and UTSMOM strategies using lookback horizons of 1, 2, 3, 6, 9 and 12 months.

In order to assess which lookback horizon is optimal the paper compares the performance measures produced by each strategy. These are: the annualized mean return, annualized standard deviation, annualized Sharpe ratio, annualized alpha, maximum drawdown and cumulative returns. Some metrics will play a larger role in determining which lookback horizon is most appropriate, however, all the metrics provide valuable insights. The paper will elaborate on how each measure is calculated in Section 4.3.

4.2.2 The LTSMOM and LRP Strategies

As shown in Section 2.4.2, the LTSMOM portfolio returns at time $t+1$ are given by the formula:

$$r_{t,t+1}^{LTSMOM} = \frac{1}{S_t}\sum_{s=1}^{S_t}\left(sign(r_{t-h,t}^{s})\frac{30\%}{\sigma_t^{s}}r_{t,t+1}^{s}\right) - TC_{t+1} - FC_{t+1} \ ,$$

The details of each component are explained in Section 2.4.2. As well as testing the six lookback horizons mentioned above, the paper includes a risk parity portfolio using the LTSMOM return formula, setting $sign(r_{t-h,t}^{s})$ equal to 1 at all times, named the levered risk parity (LRP) strategy. The analysis of the LTSMOM and LRP strategy is first conducted without transaction costs. The reason for analysing the performance of the strategies gross of costs, is that it provides a reference point that helps identify how costs effect the performance of the strategies. Following this the paper adds transaction costs, where a sensitivity analysis is conducted which is elaborated on below. Next, the paper conducts a sensitivity analysis, which is also elaborated on, where transaction costs are fixed, and financing costs are varied. The analysis of the LTSMOM strategy concludes by analysing performance including transaction costs, financing costs and expense ratios specific to ETF's.

Transaction Cost Sensitivity

While conducting the test on lookback horizons on the LTSMOM strategy the paper simultaneously implements a sensitivity analysis with respect to the transaction costs associated with the strategy. This is performed on the LTSMOM strategy with transaction costs, excluding expense ratios and financing costs. The motivation for conducting this part of the analysis without expense ratios and financing costs is to maximize generalizability of the results and to isolate the effect of transaction costs. Since a significant amount of securities are traded without expense ratios, it seems of greater utility to apply the sensitivity analysis in this manner.

The paper conducts the sensitivity analysis by calculating the performance measures for three values of the broker fee, 0.05%, 0.1% and 0.5% of the transaction size which represent an *optimistic* case, a *neutral* case and a *pessimistic* case, respectively. While the parameter being tweaked is the broker fee, the manipulation can be viewed differently. For instance, the 0.5% broker fee could equally represent a 0.4% broker fee and bid-ask spreads that are increased by 0.1%. Therefore, the sensitivity analysis captures a general increase in transaction costs and should not simply be viewed as broker cost sensitivity.

As mentioned in Section 3.1.2 the quoted broker fee on a number of online trading platforms is 0.1% and is therefore used as in all other stages of the analysis and represents the neutral case. Nonetheless, broker fees in the real world may be slightly higher or perhaps even lower. Testing the performance of the strategies at 0.5% could then still be considered a realistic, albeit high fee. As is clear, the difference between the transaction costs of the optimistic and neutral case is chosen to be small, at only 5 basis points (bps). The difference between the neutral case and the pessimistic case is larger at 40 bps. The reason for using different size increments is to extract as much information as possible from a sensitivity analysis using only three states. By using very different increments it is possible to observe how the magnitude of an increase in transaction costs influences performance.

Financing Cost Sensitivity

To assess the impact of financing costs, a sensitivity analysis will be conducted. As with transaction costs, *optimistic*, *neutral* and *pessimistic* scenarios are created where the cost of borrowing is the risk-free rate at time t, plus an annualized premium of 1%, 2.5% and 5%, respectively. The analysis is conducted on the levered strategies including bid-ask costs and a broker fee of 0.1%. The reason for including transaction costs in the sensitivity analysis is that an investor will with certainty be exposed to these in the real world. Furthermore, since the paper provides results where only transaction costs are accounted for, it is still possible to observe the specific effects that financing costs have on strategy performance. The way these costs are implemented in the LTSMOM strategy have been explained in Section 2.4 of the paper. As explained in Section 3.1.2, a financing cost of the risk-free rate plus an annualized premium of 2.5% has been identified as an obtainable financing rate. For this reason, it represents the neutral case and will be used in other sections of the analysis moving forward. The optimistic case is set to an annualized premium of 1%. While it has not been possible to find an online broker offering such a low rate, it is not unlikely that some individual investors may be able to obtain this rate. Developing a relationship with a broker over time may lead to more favourable interest rates. Moreover, as investment size increases, perhaps lower rates can be negotiated. The pessimistic case with the annualized premium of 5% also seems realistic. While better rates exist, other factors may cause an investor to be subject to this higher rate. Rates may even increase in the future. The leveraged strategies will be analysed in each scenario which will provide insights into their sensitivities to financing costs.

The LTSMOM and LRP with All Costs

The paper compares the performance of LTSMOM and LRP strategies including bid-ask costs, a 0.1% broker fee, a 2.5% financing premium and expense ratios specific to ETFs. The paper adjusts the excess returns of the strategy by subtracting the monthly expense ratios specific to each ETF. At this stage, the paper determines the optimal lookback horizon for the LTSMOM strategy which is used in the final section of the analysis where a comparison is made between a selection of other strategies.

4.2.3 The UTSMOM and URP Strategies

Given that leverage may not be available or desirable to all individual investors, the paper analyses the performance of unlevered strategies. The paper follows similar procedures in analysing the unlevered strategies as is performed with levered strategies, with a few exceptions. Here the formula derived in Section 2.4.2 is used to create the UTSMOM strategy which is:

$$r_{t,t+1}^{UTSMOM} = \frac{1}{S_t} \sum_{s=1}^{S_t} \left(sign\left(r_{t-h,t}^{s}\right) \frac{\sigma_{t,s}^{-1}}{\sum_i \sigma_{t,s}^{-1}} r_{t,t+1}^{s} \right) - TC_{t+1} \ ,$$

Here the paper analyses the performance of the UTSMOM strategies with different lookback horizons and the URP strategy. This part of the analysis is more concise than that conducted on the leveraged strategies. In this case, the paper only tests the UTSMOM and URP strategies without transaction costs, with transaction costs, and with transaction costs and expense ratios. The reason for investing the strategies by incrementally adding costs follows the same logic as before. The paper does not report a transaction sensitivity analysis in this case. These results can be observed in Appendix XX. The reason for omitting the sensitivity analysis in the main text is cost benefit related. The additional insights that the analysis provides does not warrant the space that it would consume. presentation of the unlevered strategies with transaction costs excluding expense ratios is that it provides no additional insights beyond the analysis of the leveraged strategies. For the same reason, no sensitivity analysis of transaction costs is presented on the unlevered strategies. The optimal lookback horizon will be identified while analysing the strategies including transaction costs and expense ratios. Again, the paper adjusts the excess returns of the strategy by subtracting the monthly expense ratios specific to each ETF. As with the unlevered strategies, this UTSMOM strategy will be used in a comparison with other investment strategies.

4.2.4 Comparing Strategies

After having identified the optimal lookback horizon for the LTSMOM and UTSMOM strategies as well as constructing the LRP and URP portfolios, the paper proceeds to compare the performance of these strategies against two other simple asset allocation strategies. These are the 60/40 portfolio and the equally weighted (EW) portfolios. The 60/40 portfolio allocates 60% of its weight to stocks and 40% to bonds. The EW portfolio assigns equal weight to each asset in the portfolio. Both the 60/40 and the EW portfolio are rebalanced on a monthly basis to maintain their respective weight allocations. As with the other portfolios, this rebalancing procedure is subject to transaction costs.

The EW returns are calculated in the following way:

$$r_{t,t+1}^{EW} = \frac{1}{S}\sum_{s=1}^{S} r_{t,t+1}^{s} - TC_{t+1}\ , \tag{4.2}$$

Where TC_{t+1} is calculated using Equation 2.16 and the weight notation follows the same logic as described in Section 2.4.3. The weights used in the calculation of TC_{t+1} for the EW strategy are calculated as follows:

$$w_{t+1}^{s} = \frac{1}{S}\ , \tag{4.3}$$

$$w_{t+}^{s} = \frac{\frac{1}{S}(1 + r_{t,t+1}^{s})}{\sum_{s=1}^{S}\frac{1}{S}(1 + r_{t,t+1}^{s})}\ , \tag{4.4}$$

Where S represents the number of assets and is not contingent on time.

The 60/40 returns are calculated using the formula:

$$r_{t,t+1}^{60/40} = 0.6 * \frac{1}{E}\sum_{e=1}^{E} r_{t,t+1}^{e} + 0.4 * \frac{1}{B}\sum_{b=1}^{B} r_{t,t+1}^{b} - TC_{t+1}\ , \tag{4.5}$$

Where E represents the number of equity index ETFs and B is the number of bond index ETFs. For the 60/40 strategy TC_{t+1} is calculated as follows:

$$TC_{t+1} = \sum_{e=1}^{E}\left(|w_{t+1}^{e} - w_{t+}^{e}| * (BC + BA_{t+1}^{e})\right) + \sum_{b=1}^{B}\left(\left|w_{t+1}^{b} - w_{t+}^{b}\right| * \left(BC + BA_{t+1}^{b}\right)\right) \tag{4.6}$$

The weights used in the calculation of TC_{t+1} for the 60/40 strategy are calculated as follows:

$$w_{t+1}^{e} = 0.6 * \frac{1}{E} \ , \tag{4.7}$$

$$w_{t+}^{e} = \frac{0.6 * \frac{1}{E}(1 + r_{t,t+1}^{e})}{\sum_{e=1}^{E} 0.6 * \frac{1}{E}(1 + r_{t,t+1}^{e})} \ , \tag{4.8}$$

$$w_{t+1}^{b} = 0.4 * \frac{1}{B} \ , \tag{4.9}$$

$$w_{t+}^{b} = \frac{0.4 * \frac{1}{B}(1 + r_{t,t+1}^{b})}{\sum_{b=1}^{B} 0.4 * \frac{1}{B}(1 + r_{t,t+1}^{b})}, \tag{4.10}$$

The strategies subject to comparison are therefore the LTSMOM, LRP, UTSMOM, URP, 60/40 and EW strategies. Here the paper analyses the portfolios without costs and with all costs. This provides useful insights regarding the importance of accounting for costs when assessing the potential performance of an investment strategy. Ultimately, this section of the analysis seeks to identify the optimal investment strategy of those under consideration. This enables the paper to determine whether the implementation of a time-series momentum strategy can provide an individual investor with superior investment results compared to the selected comparison strategies.

4.3 Performance Measures

As explained previously, the performance measures used to compare the investment strategies are cumulative returns, mean excess returns, standard deviations, Sharpe ratios, the alpha of the strategy relative to the *market* portfolio and maximum drawdowns. The following section will describe how each of these metrics is calculated.

4.3.1 Annualized mean excess return

One of the key performance metrics used to compare investment strategy performance will be excess returns. The annualized mean excess return for the entire sample period is calculated using the formula

$$\bar{r}_{annual}^{p} = 12 \times \frac{1}{n} \sum_{i=1}^{n} r_{i}^{p} \tag{4.11}$$

Where the average monthly excess return of portfolio strategy *p,* over the total number of monthly observations *n* is multiplied by 12 to provide the annualized mean return.

4.3.2 Annualized Standard Deviations

The standard deviation represents the volatility of the portfolio. As explained in Section 2.1 investors are not only concerned with the return of a portfolio, but also its volatility. The higher the volatility of a portfolio, the greater the risk associated with the investment. It is therefore desirable to realize a low portfolio volatility. This metric is, therefore useful in comparing the risk associated with each portfolio and, together with the portfolio returns and SR, contribute to a useful view of the risk-return characteristics of the portfolio.

As a step towards calculating the standard deviation, the variance is identified. The sample variance for each investment strategy over the entire sample period, using excess returns, is calculated using the formula

$$\sigma_p^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(r_i^p - \bar{r}^p\right)^2 \tag{4.12}$$

Where the term $1/n-1$ accounts for the degrees of freedom bias that arises due to the use of a sample arithmetic average.

The sample standard deviation is then calculated by simply taking the square root of the variance:

$$\sigma_p = \sqrt{\sigma_p^2} \tag{4.13}$$

Which is then annualized in the following equation:

$$\sigma_p^{annual} = \sqrt{12} \times \sigma_p \tag{4.14}$$

4.3.3 Annualized Sharpe Ratios

The Sharpe ratio is a useful performance metric since it portrays the risk adjusted return of a portfolio, which makes it easily comparable across portfolios that may have very different combinations of returns and standard deviations. The SR will be one of the performance metrics that receives most attention in the analysis. However, it is still of importance to assess the individual components of the metric, as described above, since some portfolios may have high SR's that are driven primarily by low volatilities. While this may suite some investors, others may be dissatisfied with low returns, despite undertaking little risk. Therefore, assessing the SR along with returns and volatilities provides a greater degree of nuance to the analysis.

The standard formula for calculating the Sharpe ratio is:

$$SR = \frac{r_t - r_f}{\sigma_p} \tag{4.15}$$

Where the term $r_p - r_f$ denotes the excess return of portfolio *p*. Since excess returns are calculated prior to the commencement of the analysis and used throughout the analysis, the annualized Sharpe ratio is simply calculated as follows:

$$SR_{annual} = \sqrt{12} \times \frac{\overline{r_p}}{\sigma_p} \tag{4.16}$$

Where $\overline{r_p}$ is the mean excess return of portfolio p, σ_p is its standard deviation of the excess returns and the monthly SR is annualized by multiplying it by $\sqrt{12}$.

4.3.4 Cumulative excess returns

Purely for readability, the paper presents cumulative excess return plots using an initial investment of \$100. Cumulative excess returns, with an initial investment of \$100 are then calculated in the following way:

$$r_{t,t+n} = 100 \times \left(1 + r_{t,t+1}\right) \times \cdots \times \left(1 + r_{t+n-1,t+n}\right) \tag{4.17}$$

Where the annualized mean return is displayed as a single number, a cumulative returns plot enables the paper to observe how well a strategy performs at different points in time. This is useful for identifying how well a strategy performs in a market downturn, for instance.

4.3.5 Alpha

Another important measure of strategy performance is the portfolios alpha. As explained in Section 2.1, alpha represents the possible abnormal excess return that a portfolio has realized compared to common factors. Alpha is calculated by regressing the historical excess returns onto a chosen set of common factors. Following the literature (see Moskowitz et al. (2012) and Pedersen (2015)), the chosen factors are the MSCI World Index and the Barclays Aggregate Bond Index. Other studies use a greater number of factors, however, since the universe of assets under inspection in this paper consist only of equities and bonds, it seems appropriate to exclude these factors. The regression takes the following form:

$$r_t^p = \alpha + \beta_1 MKT_t + \beta_2 BOND_t + \varepsilon_t \tag{4.18}$$

Here, r_t^p is the excess return of strategy p, MKT represents the MSCI World Index excess returns and $BOND$ is the Barclays Aggregate Bond Index excess returns. The monthly alpha is then annualized:

$$\alpha_{annual} = 12 * \alpha \tag{4.19}$$

The value of alpha on its own is not enough to claim that abnormal excess returns are realized. To substantiate the claim that abnormal excess returns are present, the significance of alpha must be tested. To this end a *t*-test must be performed on alpha to determine whether it is significantly different from zero. The standard Student t-test would likely be inconsistent in this regression since the error term ε_t^s is possibly both heteroskedastic and correlated over time. Therefore, heteroskedasticity and autocorrelation-consistent (HAC) standard errors provide a more accurate calculation of the *t*-statistics. HAC standard errors or *clustered standard errors* are useful in this setting, since they allow for random autocorrelation and heteroskedasticity within an entity, while treating the errors as uncorrelated across entities (Stock & Watson, 2015, p. 413). Therefore, the paper implements a the *t*-test using heteroskedasticity and autocorrelation consistent (HAC) standards errors developed by Newey and West (1987). These are commonly referred to as Newey-West standard errors. Formally, the null hypothesis that alpha is not significantly different from zero is tested, with the alternative hypothesis that it is:

$$H_0: \alpha = 0$$

$$H_1: \alpha \neq 0$$

The *t*-test is calculated using the formula (Stock & Watson, 2015):

$$t = \frac{\bar{\alpha}_{observed} - \alpha_{theoretical}}{SE_{NW}(\bar{\alpha}_{observed})} \quad , \tag{4.20}$$

Since, according to the theory presented in Section 2.1, $\alpha_{theoretica}$ is equal to zero, the formula reduces to:

$$t = \frac{\bar{\alpha}_{observed}}{SE_{NW}(\bar{\alpha}_{observed})} \quad . \tag{4.21}$$

This paper will follow standard convention and require a p-value of 0.05 for determining statistical significance. Therefore, if $|t| > 1.96$ then the null hypothesis, $H_0: \bar{r}_{annual}^v = 0$ is rejected and the alternative hypothesis, $H_1: \bar{r}_{annual}^v \neq 0$ is accepted. A rejection of the null hypothesis means that the annualized mean return is significantly different from zero at the 5% level. A significant and positive alpha mean that the investment strategy displays abnormal positive returns.

4.3.6 Maximum drawdown

A risk measure commonly used to evaluate hedge fund strategies is the maximum drawdown over a given period of time (Pedersen, 2015). A component used to calculate the maximum drawdown is the hedge fund's high water mark (HWM), defined as the highest price it has realized in a specific time-frame. Formally:

$$HWM_t = \max_{s \leq t} P_s \tag{4.22}$$

A drawdown (DD) is then defined as the cumulative loss since losses commenced (Pedersen, 2015). The DD in percentage terms is then defined as:

$$DD_t = \frac{HWM_t - P_t}{HWM_t} \tag{4.23}$$

where the cumulative return at time t is represented by P_t. The DD is the amount that has been lost since the peak. Intuitively then, the maximum drawdown (MDD) is the largest DD that has been experienced during a given time-frame and is written formally:

$$MDD_T = \max_{t \leq T} DD_t \tag{4.24}$$

A large *MDD* indicates that a strategy may be susceptible to large losses, which is obviously not an attractive attribute from an investor perspective. A large MDD shows that an investment strategy performs badly given a certain event and losses may be so large that even if the strategy performs well in most scenarios, its vulnerability to specific events may render it too risky to implement. This of course, will depend on many things such as investment horizon, risk aversion, and so on.

5 ANALYSIS

This section of the paper analyses the data following the methodology outlined in Section 4. The paper conducts a pooled panel autoregression to determine whether price continuation is present in the data in Section 5.1. Following this, Section 5.2 analyses the LTSMOM strategy, performing various tests to identify the optimal lookback horizon, determine the strategy's robustness to costs and gain insights regarding the benefits of using time series momentum signals. In almost identical fashion, the paper analyses the performance of the UTSMOM strategy in Section 5.3. Finally, Section 5.4 compares the performance measures of the time series momentum strategies to standard asset allocation strategies and determines whether the they produce superior performance.

5.1 THE PRESENCE OF PRICE CONTINUATION

Following the methodology outlined in Section 4.1, the paper tests for the presence of price continuation in the data. The *t*-statistics obtained from the pooled panel autoregression are shown in Figure 5.1. The *t*-statistic of the first month is positive, however, it is not statistically significant. This indicates that the previous months performance does not provide any information as to how the performance will be in the current month. The performance from 2, 3, 4 and five months prior to the current month display significant positive return continuation, suggesting that time-series momentum is present in the data. The 6, 7- and 8-month lags are not statistically significant, whereas the 9-month lag is positive and statistically significant. There is evidence of a momentum reversal with the 11- and 13-month lags producing statistically significant negative *t*-statistics. Beyond the 13th month lag the results are difficult to draw any meaningful insights from, oscillating between positive and negative *t*-statistics in an almost random pattern.

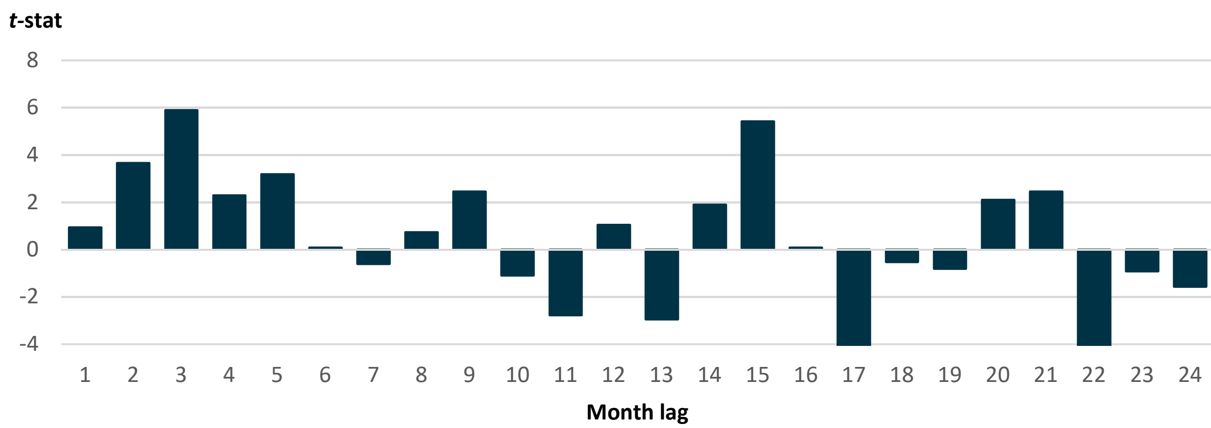


Figure 5.1 *t*-statistics of the pooled panel regression, lagged 24 months

There is evidence that price continuation is present in the data. However, the dynamics of this continuation are different from the results found by Moskowitz et al. (2012), who find stronger and more persistent *t*-statistics over the first 12 months. The weaker trend signals observed in this data are in alignment with the findings of Hurst et al. (2017) who argue that clear trends have been elusive in recent years. The paper discusses these findings in more depth in Section 6.1.

5.2 The LTSMOM and LRP Strategies

The paper now investigates the performance of the LTSMOM and LRP strategies following the methods described in Section 4.2. The paper begins by analysing the performance of the levered strategies gross of costs. Thereafter, the paper performs the transaction cost sensitivity analysis. The paper then conducts the financing cost sensitivity analysis. Finally, the paper analyses the performance of the strategies net of transaction cost, financing costs and expense ratios.

5.2.1 The LTSMOM and LRP Strategies without Costs

The performance measures for the LTSMOM and LRP strategies gross of costs are reported in Table 5.1 and cumulative returns are displayed in Figure 5.2.

Table 5.1

Performance of LTSMOM and LRP Strategies without Transaction Costs

	1m	2m	3m	6m	9m	12m	LRP
Average excess return	4.2%	7.6%	9.0%	8.3%	8.7%	7.9%	9.6%
Volatility	10.8%	11.5%	12.0%	12.5%	12.2%	12.9%	17.8%
Sharpe Ratio	0.39	0.66	0.75	0.67	0.71	0.61	0.54
Annualized Alpha	2.2%	5.6%	7.1%	6.2%	6.6%	5.9%	5.2%
t-Statistic	0.91	2.17	2.57	2.17	2.33	2.00	2.11
Max Drawdown	29.3%	21.9%	23.0%	25.5%	21.1%	26.8%	43.0%

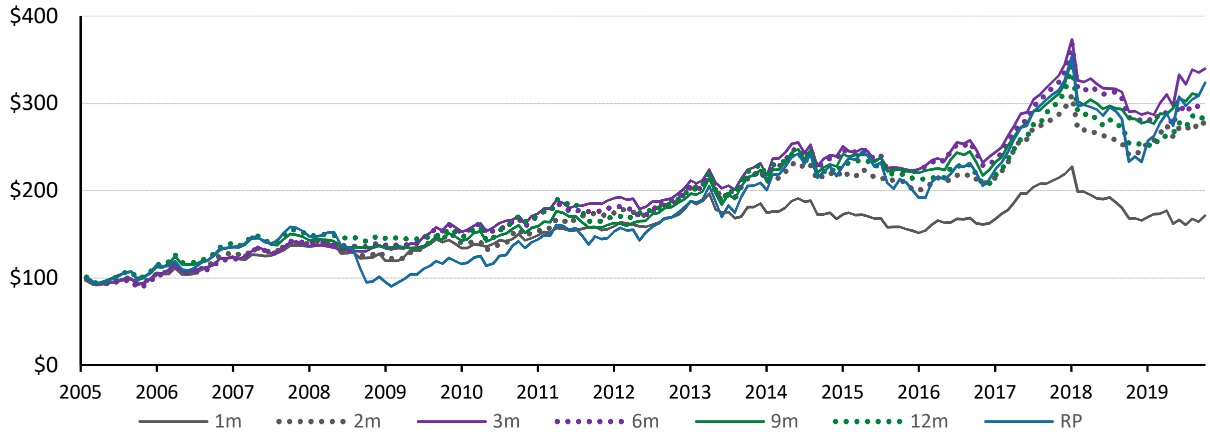


Figure 5.2. Cumulative excess returns of LTSMOM and LRP strategies without transaction costs from January 2004 to October 2019

At a glance, it can be constituted that the LTSMOM strategy with a 1-month lookback horizon is inferior to its counterparts. This strategy displays the worst performance measures in almost every case when viewed against the other LTSMOM strategies. Only in terms of volatility does this strategy perform best. It also performs worse than the LRP strategy in every aspect other than volatility and maximum drawdown (MDD). Figure 5.2 further highlights the inferiority of this strategy, where the it clearly lags behind the other strategies. The results from the pooled panel regression reported in Figure 5.1 show that a 1-month lag does not produce statistically significant price continuation. Therefore, it is not surprising that the 1-month strategy performs poorly. Although it is too early to constitute anything regarding the strategies, since no costs have been implemented yet, it is not expected that this strategy will improve moving forward. On the contrary, as highlighted by Pedersen (2015, p. 225) transaction costs are higher for strategies using shorter lookback horizons.

The remaining five LTSMOM strategies are more closely aligned than the 1-month strategy and require closer inspection to reveal which one produces the best performance results. In terms of excess returns, the 3-month strategy outperforms its LTSMOM counterparts with an excess return of 9%. The LTSMOM strategy that displays the lowest volatility besides the 1-month strategy is the 2-month strategy. In terms of risk-adjusted returns 3-month strategy produces the best result with a Sharpe ratio (SR) of 0.75. With an SR of 0.71, the 9-month strategy performs second-best. All LTSMOM strategies, besides the 1-month strategy produce significant and positive alphas relative to the market, which was defined as the MSCI World Index and Barclays Aggregate Bond Index in Section 4.3.5. The 3-month strategy produces the best annualised alpha of 7.1%, with a *t*-statistic of 2.57. The 9-month strategy is second-best again with an alpha of 6.6% and a corresponding *t*-statistic of 2.33. At 21.1%, the 9-month strategy has the lowest MDD. However, the MDD of the 3-month strategy is 23%, which is only 190 bps larger than the 9-month strategy. Given that the 3-month strategy produces the best excess return, SR and alpha, and that its MDD is comparatively low, the paper argues that the 3-month strategy performs best in a holistic sense. The identification of the 3-month strategy as the optimal when excluding costs is interesting considering that Moskowitz et al. (2012) find the 12-month lookback horizon to be optimal for their TSMOM strategy. Several factors may influence the difference in results which the paper discusses in Section 6.1.

Having identified the 3-month strategy as optimal, the paper will compare its performance measures with the LRP strategy. The LRP strategy has a higher excess return than the 3-month LTSMOM strategy, at 9.6%. However, with a volatility of 17.8%, the LRP strategy is riskier than the 3-month strategy which has a more subdued volatility of 12.0%. The effect of this difference in volatility is clearly visible in the resulting SRs. Here, the 3-month strategy produces an SR of 0.75, whereas the LRP displays an inferior 0.54. This shows that the higher return attached to the LRP strategy is achieved only by taking on more risk. The LRP strategy realizes a significant alpha at 5.2% with a *t*-statistic of 2.11, however, this is lower than that of the 3-month strategy which has an alpha of 7.1% and *t*-statistic of 2.57, as already mentioned. The existence of abnormal excess returns questions the assumptions of the CAPM. However, since costs have not been accounted for so far, the paper will refrain from drawing any conclusions on this subject yet.

The MDD of the LRP is far higher than that of the 3-month strategy, at 43% and 23%, respectively. With an MDD 20 percentage points higher than the 3-month strategy, the LRP strategy poses a far higher risk of large losses which is obviously undesirable for an investor. That the MDD is higher for the LRP than the 3-month strategy makes good sense. By construction, the 3-month strategy does not invest in assets with negative average excess returns over the past months. As can be seen in Figure 5.2, during the Global Financial Crisis (GFC) around 2008, the LRP strategy realizes significant losses. These losses are avoided by the LTSMOM strategies, particularly those with longer lookback horizons. During the GFC the LTSMOM strategies likely have very little wealth invested in the assets due to the long and continuous period with losses. This explains the relatively flat cumulative returns in that period. Contrarily, the LRP strategy, being long all assets is punished during the GFC. The Long-short TSMOM strategies investigated by Moskowitz et al. (2012) display significant gains during the GFC. The reason for this difference is that where the long-only LTSMOM strategy excludes poor past performers from the portfolio, the long-short TSMOM strategy shorts them, realizing impressive gains due to the continuation of poor performance. While the long-only LTSMOM strategy foregoes these gains, it remains shielded from the significant losses that other strategies such as the LRP suffer. While the LTSMOM avoids significant losses during the GFC, it suffers almost as much as the LRP strategy during the market corrections of 2018 (Fisher, 2019). As highlighted by Moskowitz et al. (2012), the TSMOM strategy performs badly when there are sudden reversals in the market. While the LTSMOM strategies are not protected from the corrections of 2018, they do not suffer extreme losses that would likely be the case if they held short positions.

Clearly, since the only difference between the LTSMOM strategies and the LRP strategy is the use of time-series momentum signals, this is the only possible source of the superior performance. Therefore, for the paper portfolio, it can be concluded that using a 3-month lookback horizon, the LTSMOM strategy performs above and beyond the LRP strategy. However, given the anticipated reduction in performance due to transaction costs, a real-life implementation may provide different results. This is the subject of investigation in the following subsection.

5.2.2 Sensitivity Analysis of Transaction Costs

Excluding transaction costs, the paper finds that the 3-month LTSMOM strategy produces the best performance, both in comparison to other lookback horizons and the LRP strategy. Lesmond et al. (2004) argue that momentum strategies are not robust to transaction costs. To investigate this the paper now conducts a transaction cost sensitivity analysis which is implemented following the methodology presented in Section 4.2.2. Table 5.2 summarizes the performance measures of all three transaction cost scenarios. Panel A displays the results for the optimistic case, the neutral case is shown in Panel B and the pessimistic case is presented in Panel C. Following the same order, the corresponding cumulative returns plots are shown in Figure 5.3.

Table 5.2 shows that as transaction costs increase excess returns are reduced. The effects are most severe for strategies using short-term signals and have a smaller impact on the strategies with longer look-back horizons. The effects are not severe in the optimistic case, where broker fees are 0.05%. Here the excess return for the 3-month strategy is 8.4%, down only 60bps from its costless state. The 12-month strategy, on the other hand, only drops 40 bps registering an excess return of 7.5%. Transitioning from the optimistic to the neutral scenario where broker fees are 0.1% the 3-month strategy again loses 60 bps recording an excess return of 7.8%. Here the excess return of the 12-month strategy is only reduced by 20 bps. Returns are more than halved for the 3-month strategy as broker fees increase from 0.1% to 0.5%. The 40 bps increase in transaction costs reduces the return of the 3-month strategy by 430 bps, from 7.8% to 3.5%. For the same transition, the 12-month strategy experiences a more subdued decline of 280 basis points, from 7.2% to 4.4%. The strategy with returns most resilient to transaction costs is the LRP, suffering a reduction of only 160 bps, from 9.1% to 7.5%.

Table 5.2

Performance measures of the LTSMOM strategies with different lookback horizons and the LRP strategy with bid-ask transaction costs and varying broker fees. Panel A shows the performance measures with a 0.05% broker fee. Panel B shows the measures with a 0.1% broker fee. Panel C uses a broker fee of 0.5%.

Panel A: 0.05% Broker Fee

	1m	2m	3m	6m	9m	12m	LRP
Average excess return	2.7%	6.6%	8.4%	7.7%	8.2%	7.5%	9.3%
Volatility	10.9%	11.5%	12.1%	12.5%	12.2%	13.0%	17.8%
Sharpe Ratio	0.25	0.57	0.70	0.62	0.68	0.58	0.52
Annualized Alpha	0.8%	4.6%	6.4%	5.7%	6.1%	5.5%	4.9%
t-Statistic	0.30	1.76	2.34	1.97	2.17	1.86	2.01
Max Drawdown	31.5%	22.7%	23.5%	26.2%	21.6%	27.2%	43.2%

Panel B: 0.1% Broker Fee

	1m	2m	3m	6m	9m	12m	LRP
Average excess return	1.4%	5.7%	7.8%	7.3%	7.8%	7.2%	9.1%
Volatility	11.0%	11.6%	12.1%	12.5%	12.2%	13.0%	17.8%
Sharpe Ratio	0.13	0.49	0.65	0.58	0.64	0.55	0.51
Annualized Alpha	-0.6%	3.7%	5.9%	5.2%	5.7%	5.1%	4.7%
t-Statistic	-0.22	1.41	2.14	1.80	2.03	1.74	1.93
Max Drawdown	34.4%	23.5%	23.9%	26.8%	22.0%	27.6%	43.3%

Panel C: 0.5% Broker Fee

	1m	2m	3m	6m	9m	12m	LRP
Average excess return	-9.2%	-1.6%	3.5%	3.4%	4.7%	4.4%	7.5%
Volatility	11.8%	12.0%	12.2%	12.8%	12.3%	13.1%	17.9%
Sharpe Ratio	-0.78	-0.13	0.29	0.27	0.38	0.34	0.42
Annualized Alpha	-11.1%	-3.5%	1.6%	1.4%	2.6%	2.4%	3.2%
t-Statistic	-3.97	-1.26	0.57	0.48	0.91	0.80	1.27
Max Drawdown	77.8%	43.0%	27.2%	31.3%	25.2%	30.7%	44.1%

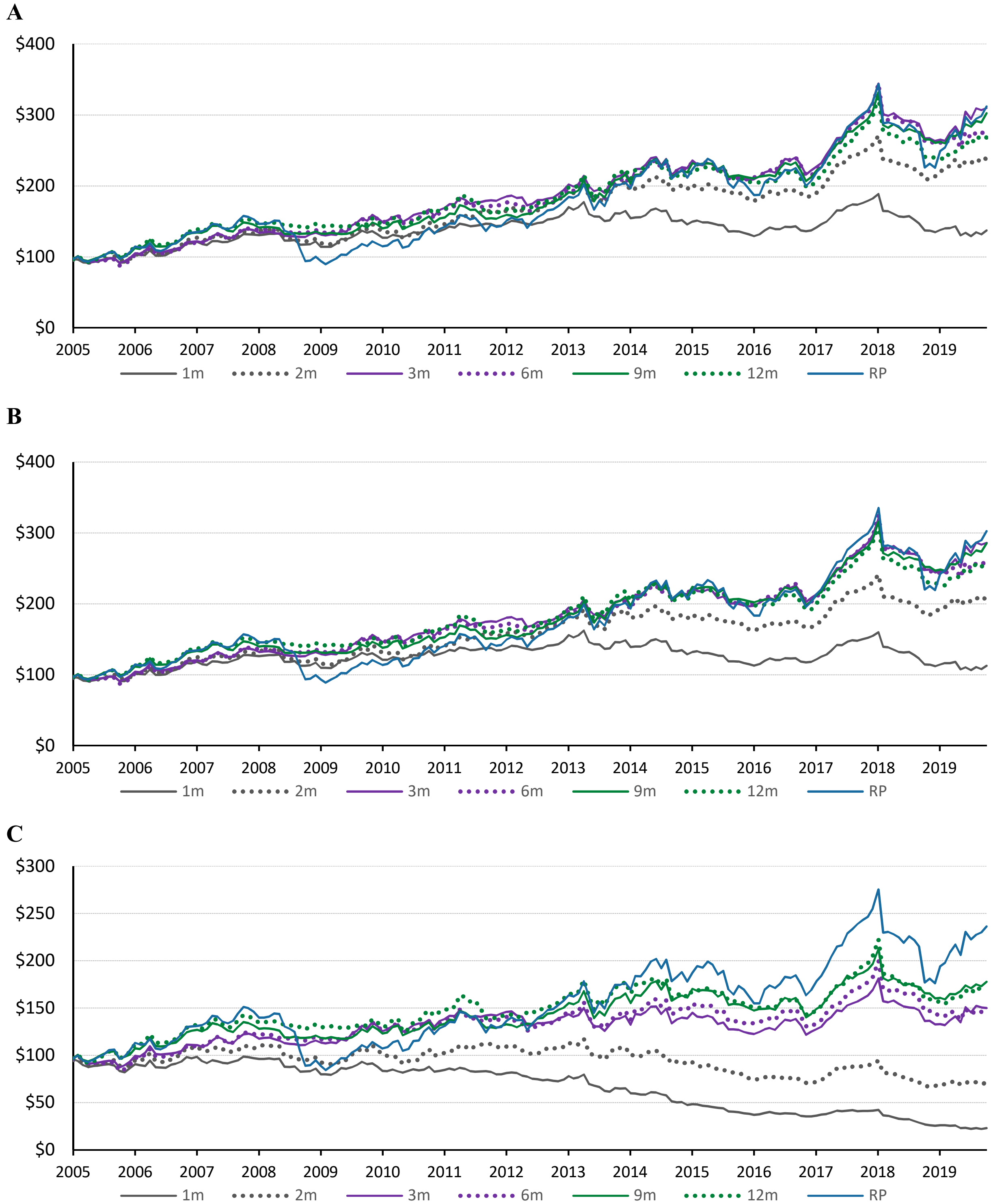


Figure 5.3. Cumulative excess returns of the LTSMOM and LRP strategies. Panel A shows the performance with bid-ask transaction costs and a 0.05% broker fee. Panel B shows the performance with bid-ask transaction costs and a 0.1% broker fee. Panel C shows the performance with bid-ask transaction costs and a 0.5% broker fee.

While volatilities do increase slightly, the effects are negligible. With falling returns and stable volatilities all strategies experience declining SRs. This can be seen in Figure 5.4, which also includes SRs for the strategies gross of costs. Here the SRs pertaining to the 1-month and 2-month strategies experience sharp declines compared to the much flatter descent visible in the 9-month and 12-month strategies.

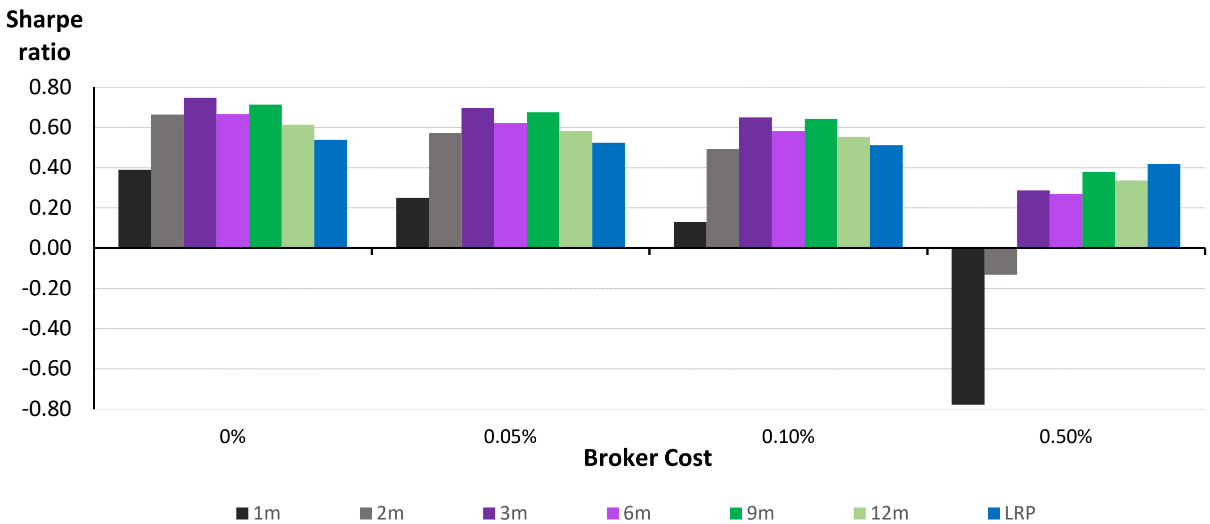


Figure 5.4 Sharpe ratio sensitivity to changes in broker costs of the LTSMOM and LRP strategies

In the positive case, with broker costs at 0.05%, the 3-month strategy continues to produce a superior SR of 0.70. This is also the case in the neutral scenario where the 3-month strategy has an SR of 0.65 and the 9-month strategy records an SR of 0.64. In the neutral scenario the LRP strategy still underperforms the majority of LTSMOM strategies, surpassing only the 1-month and 2-month strategies. In the pessimistic case, however, the impact of transaction costs is clearly visible. In this instance, the optimal lookback horizon is no longer three months. Here, the LRP strategy produces the best SR of 0.42. The LTSMOM strategy recording the best SR of 0.38 is the 9-month strategy, followed by the 12-month strategy with an SR of 0.34. In this scenario the SR of the 3-month strategy is 0.29.

Annualized alphas follow the same trend as SRs. Interesting to note, is that even in the optimistic case, only three strategies continue to display significant alphas. Specifically, the 3-month, 9-month and LRP strategies produce *t*-statistics of 2.34, 2.17 and 2.01, respectively. In the neutral strategy, only the 3-month and 9-month strategies retain significant alphas with *t*-statistics of 2.14 and 2.03, respectively. In the pessimistic case, no strategy realizes a statistically significant alpha. The robustness of the alphas in the neutral case, which the paper has identified as realistic, again questions the assumptions of the CAPM. However, the paper can still not conclude anything since financing costs and expense ratios are yet to be accounted for.

MDDs are also affected more significantly for short-term signal strategies than for those with longer-term signals. The LRP displays the greatest resilience to transaction costs in this case too. The 1-month strategy exhibits huge sensitivity, seeing its MDD more than double when transitioning from a broker cost of 0.1% to 0.5%. Here the MDD increases from 34.4% to 77.8%. Viewing this development along with Panel C in Figure 5.3, it is apparent that this is because with broker costs at 0.5%, the 1-month strategy almost consistently realizes negative cumulative returns. Hence, as transaction costs increase, not only does the 1-month strategy underperform the other strategies, it corrodes wealth. The 2-month strategy exhibits a similar, albeit less severe tendency. However, in all scenarios the remaining LTSMOM strategies still outperform the LRP strategy in terms of MDD. The 9-month strategy performs best in all scenarios with respect to MDD, closely followed by the 3-month strategy. Although the LRP strategy is less sensitive to transaction costs than the LTSMOM strategies, it continues to exhibit a far higher MDD.

The cumulative returns graphs shown in Figure 5.3 provide an illustration of the changing dynamics of the strategies as transaction costs increase. Panel A and Panel B of Figure 5.3, representing broker costs of 0.05% and 0.1%, respectively, are almost identical. Here the 1-month and 2-month strategies clearly underperform all other strategies. The LRP strategy and the LTSMOM strategies with lookback horizons of 3-months and above display very similar performance dynamics in these two scenarios. However, as broker cost increases to 0.5%, significant differences in performance are observable. Panel C of Figure 5.3 shows that in this scenario the LRP strategy produces the highest cumulative return over the sample period, followed by the 12-month and 9-month strategies. These findings are in line with what Pedersen (2015) would predict, namely that strategies using shorter signals are impacted more significantly by transaction costs than those using longer signals. These finding highlight the importance of accounting for transaction costs prior to strategy implementation. The optimal lookback horizon cannot be taken for granted, since it varies depending on the size of transaction costs. For the remainder of the analysis the paper uses broker costs of 0.1%, corresponding to the neutral case. In this scenario, the 3-month strategy performs best and displays results that are robust to transaction costs. This contradicts the findings of Lesmond et al. (2004), who argue that momentum strategies are not robust to transaction costs. The paper discusses this further in Section 6.2.

5.2.3 Sensitivity Analysis of Financing Costs

As highlighted by Asness et al. (2012) high financing costs may prevent some investors from using leverage in their investment strategies. Therefore, the focus of this subsection is to uncover the degree to which financing costs reduce the performance of the LTSMOM and LRP strategies. As with transaction costs, the paper conducts a sensitivity using three scenarios following the methodology presented in Section 4.2.2. The performance measure results of this analysis are presented in Table 5.3. Cumulative excess returns graphs are shown in Figure 5.5.

Table 5.3 Performance of LTSMOM and LRP Strategies with Bid-Ask Transaction Costs, a 0.1% Broker Fee and Financing costs. Panel A shows results with an annualized 1% premium. Panel B uses a 2.5% premium. Panel C applies a 5% premium

Panel A: 1% Financing Premium

	1m	2m	3m	6m	9m	12m	LRP
Average excess return	-0.1%	4.0%	6.0%	5.4%	5.9%	5.2%	5.9%
Volatility	11.0%	11.5%	12.1%	12.5%	12.2%	13.0%	17.8%
Sharpe Ratio	-0.01	0.35	0.50	0.43	0.48	0.40	0.33
Annualized Alpha	-2.1%	2.1%	4.1%	3.3%	3.8%	3.1%	1.6%
t-Statistic	-0.84	0.79	1.47	1.15	1.34	1.06	0.63
Max Drawdown	41.7%	23.9%	24.3%	27.8%	22.5%	28.1%	44.1%

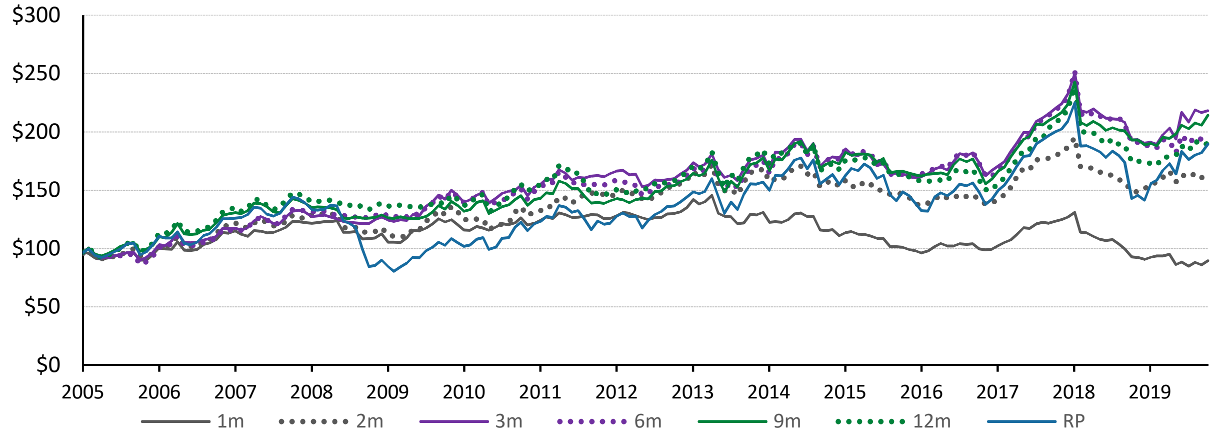
Panel B: 2.5% Financing Premium

	1m	2m	3m	6m	9m	12m	LRP
Average excess return	-2.5%	1.6%	3.2%	2.6%	3.0%	2.2%	1.2%
Volatility	11.0%	11.4%	12.1%	12.6%	12.2%	13.0%	17.8%
Sharpe Ratio	-0.22	0.14	0.27	0.20	0.24	0.17	0.07
Annualized Alpha	-4.5%	-0.3%	1.3%	0.5%	0.9%	0.2%	-3.2%
t-Statistic	-1.75	-0.13	0.47	0.18	0.31	0.05	-1.26
Max Drawdown	51.2%	28.1%	24.9%	29.2%	25.8%	32.6%	45.3%

Panel C: 5% Financing Premium

	1m	2m	3m	6m	9m	12m	LRP
Average excess return	-6.3%	-2.5%	-1.4%	-2.1%	-1.9%	-2.7%	-6.7%
Volatility	11.1%	11.4%	12.3%	12.8%	12.4%	13.2%	17.9%
Sharpe Ratio	-0.57	-0.22	-0.11	-0.17	-0.15	-0.21	-0.38
Annualized Alpha	-8.3%	-4.4%	-3.3%	-4.2%	-4.0%	-4.8%	-11.1%
t-Statistic	-3.21	-1.65	-1.14	-1.38	-1.35	-1.58	-4.27
Max Drawdown	68.2%	46.5%	48.4%	50.9%	53.1%	57.1%	76.3%

A



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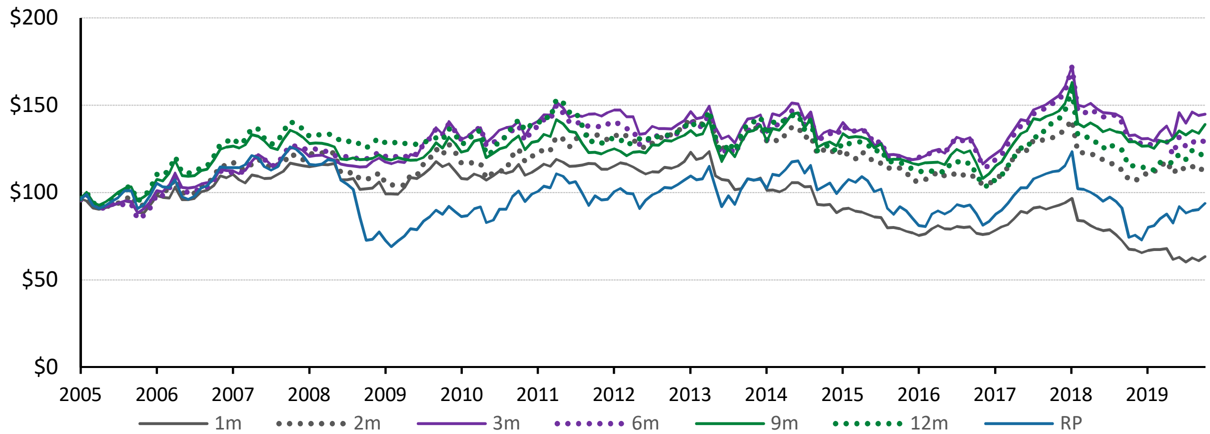

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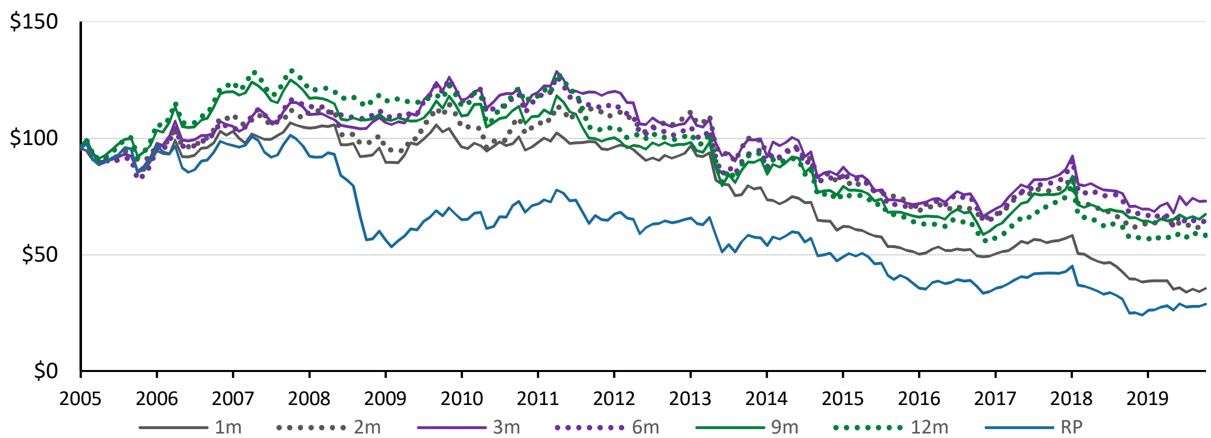


Figure 5.5. Cumulative excess returns of LTSMOM and LRP strategies with bid-ask transaction costs, a 0.1% broker fee and financing **costs.** Panel A shows the performance with a financing cost premium of 1%. Panel B shows the performance with a financing cost premium of 2.5%. Panel C shows the performance with a financing cost premium of 5%

As expected, the introduction of financing costs reduces the excess returns of the strategies. Considering first the transition from no financing costs to a 1% cost, the LRP is affected more substantially than any other strategy. The excess return of the 3-month strategy is reduced by 180 bps from 7.8% to 6%, whereas the LRP experiences a decline of 320 bps from 9.1% to 5.9%. As financing costs increase the damage to excess returns becomes completely detrimental to all strategies. As with the introduction of transaction costs, financing costs have little effect on the volatility of each strategy. With stable volatilities and falling excess returns, all strategies experience declines in SRs. Figure 5.6 illustrates these effects.

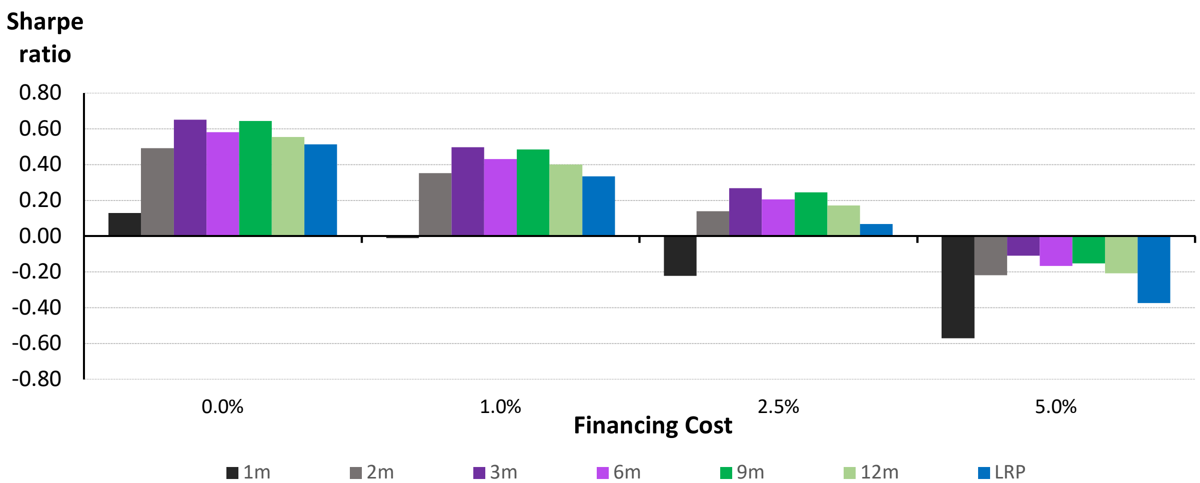


Figure 5.6 Sharpe ratio sensitivity to changes in the financing cost premium of the LTSMOM and LRP strategies

The effects of financing costs on the SRs are most pronounced for the LRP strategy. As described in Section 2.4, when an asset in the LTSMOM strategy has $sign\left(r^{s}_{t-k,t}\right)$ equal to zero, the wealth that would have been allocated to it is used to reduce external financing. Therefore, not only does that specific asset not require financing, the overall level of required borrowing is reduced. This of course reduces financing costs for the LTSMOM strategies whereas the LRP strategy which uses more leverage has higher financing costs. While the LRP strategy is penalized more radically, the effects on the LTSMOM strategies are still severe. In the optimistic scenario, the 3-month strategy, which performs best, realizes an SR of 0.5. In the neutral scenario the SR is reduced to 0.27. As mentioned, this decline in performance is driven by a reduction in excess returns. In the pessimistic case all strategies suffer from negative returns, resulting in SRs below zero.

Already in the optimistic case where financing costs are set to 1%, all *t*-statistics fail to produce statistical significance. The greatest performance in terms of alpha is the 3-month strategy with an alpha of 4.1%, followed by the 9-month strategy with an alpha of 3.8%. However, lacking statistical significance it is not possible to assert that these results are not random. Obviously, performance worsens as the financing costs increase. The dynamics of the alphas follow the same pattern as with the SR. When financing cost premiums reach 5%, all strategies have negative alphas, with the 1-month and LRP strategies producing statistical significance for these negative results. Failing to display significant alphas even in the optimistic case, means that the strategies no longer challenge the assumptions of the CAPM.

MDDs are also greatly impacted by the presence of financing costs. However, the effects are quite subdued moving from no financing costs at all to the optimistic case. As the financing costs increase, the effects become far more apparent. For instance, the 3-month strategy sees its MDD increase by only 60 bps from 24.3% to 24.9% as the financing costs increase from 1% to 2.5%. As the financing costs increase to 5%, however, the MDD rises to 48.4%, a 2350 bps increase from the neutral case. Figure 5.5 illustrates the detrimental effect that financing costs have on the strategy.

The results from the financing cost sensitivity analysis show that the performance of all strategies is greatly reduced when accounting for financing costs. Excess returns and SRs fall drastically as financing costs increase. No strategy produces a statistically significant alpha, even in the optimistic case, where the financing cost premium is 1%. MDDs also rise, reaching severe levels in the pessimistic case. From the results obtained so far, it seems that financing costs are the biggest threat strategy performance and not transaction costs. Asness et al. (2012) advocate investing in safe assets and applying leverage to increases returns. However, the authors also highlight that some investors may be unwilling or unable to use leverage. Certainly, with the effects observed in this analysis, it seems that an individual investor is unable to reap the benefits leverage due to the high costs that he must incur. This is discussed in more detail in Section 6.3.

5.2.4 The LTSMOM and LRP Strategies with All Costs

So far, the paper has examined the effects of different costs on the performance of the LTSMOM and LRP strategies both in terms of lookback horizons and performance sensitivity. Now the paper imposes asset specific expense ratios to each strategy, net of transaction and financing costs. The transaction and financing costs are 0.1% and 2.5%, respectively, consistent with the neutral strategy previously examined. Performance measures are shown in Table 5.4. Cumulative returns are presented in Figure 5.7.

Table 5.4

Performance measures of the LTSMOM and LRP strategies with bid-ask transaction costs, a 0.1% broker fee, expense ratios and a 2.5% financing cost premium

	1m	2m	3m	6m	9m	12m	LRP
Average excess return	-3.0%	1.0%	2.6%	1.9%	2.3%	1.6%	0.3%
Volatility	11.0%	11.4%	12.1%	12.6%	12.2%	13.0%	17.8%
Sharpe Ratio	-0.27	0.09	0.22	0.15	0.19	0.12	0.02
Annualized Alpha	-5.0%	-0.9%	0.7%	-0.1%	0.2%	-0.5%	-4.1%
t-Statistic	-1.96	-0.35	0.25	-0.03	0.08	-0.17	-1.62
Max Drawdown	53.1%	29.7%	26.5%	29.6%	27.0%	35.5%	47.8%

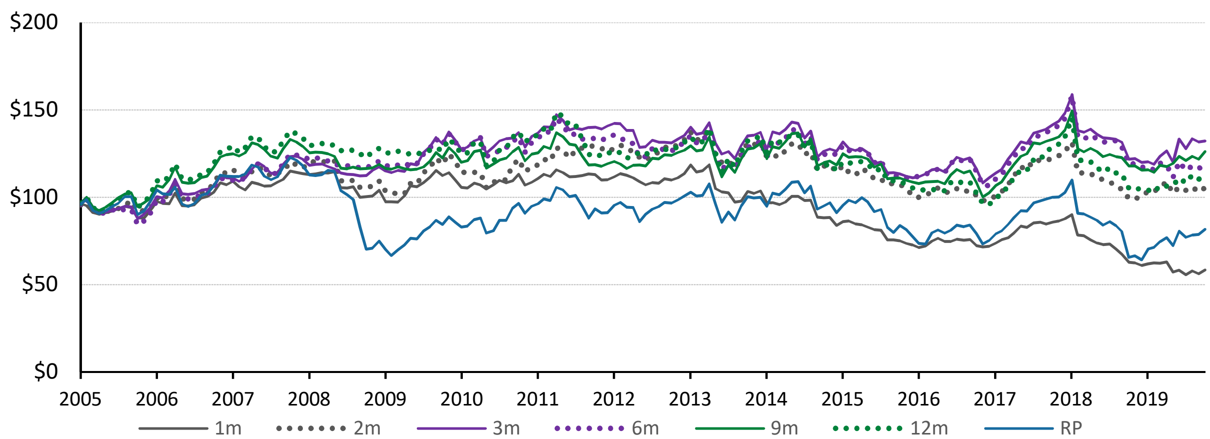


Figure 5.7 Cumulative excess returns of LTSMOM and LRP strategies with bid-ask transaction costs, a 0.1% broker fee, expense ratios and a 2.5% financing cost premium between January 2005 and October 2019

In terms of excess return, volatility and SR, the 3-month strategy outperforms it peers. Comparing the above results with those presented in Panel B of Table 5.3, which include identical costs except expense ratios, excess returns are reduced by 60 bps from 3.2% to 2.6% for the 3-month strategy. Volatility remains unchanged. The SR decreases from 0.27 to 0.22. Similar effects are observable for the other LTSMOM strategies. The LRP strategy, on the other hand is penalized more noticeably. While its volatility is unaffected, excess returns are squeezed from 1.2% to 0.3%, a reduction of 90 bps. The SR is depressed from 0.07 to 0.02. As with financing costs, the inclusion of expense ratios has a more negative impact on the LRP strategy than on the LTSMOM strategies. Again, the fact that the LRP strategy invests in all assets at all times results in higher costs, this time caused by the expense ratios.

Alphas are reduced further with only the 3-month and 9-month strategies realizing positive results. While positive in these cases, neither are of statistical significance with *t*-statistics of only 0.25 and 0.08 for the 3-month and 9-month strategies, respectively. Being so far from statistical significance, commenting on the size of the respective alphas seems unnecessary. Although the inclusion of expense ratios has reduced alphas, this cost did not deal the decisive blow. Prior to the inclusion of this cost, alphas had already lost statistical significance.

MDDs increase as expense ratios are accounted for. The 3-month strategy adds 160 bps moving from an MDD of 24.9% to 26.5%. The LRP strategy experiences a moderately higher increase of 250 bps rising from 45.3% to an MDD of 47.8%. Consistent with the other performance measures, this greater effect is likely caused by the fact that the LRP strategy remains actively invested in all assets throughout the sample period. There is no significant development in the cumulative returns due to the inclusion of expense ratio costs.

Concluding Remarks on the LTSMOM and LRP Strategies

The differences in the performance metrics observable in Table 5.1 and Figure 5.2 with those shown in Table 5.4 and Figure 5.7 highlight the importance of including costs when constructing investment strategies. When conducting back-tests to decide what investment strategy to pursue, the exclusion of these costs can potentially be very costly. In its paper form, the 3-month LTSMOM strategy seems very attractive realizing an excess return of 9.0%, an SR of 0.75 and an alpha of 7.1% with a statistically significant *t*-statistic of 2.57. An individual investor having conducted this back-test may, understandably, be tempted to implement this strategy with the expectation of realizing abnormal excess returns at a relatively low level of risk. However, accounting for transaction and financing costs, as well as expense ratios, this strategy is severely undermined. Accounting for these costs the 3-month LTSMOM strategy realizes an excess return of only 2.6%, down 640 bps from its costless state. The SR is reduced to 0.22. Alpha is reduced by 630 bps to 0.7% and is no longer statistically significant, achieving a *t*-statistic of only 0.25. The MDD is increased from 23.0% to 26.5%. These finding will be discussed further in Section 6.6.

Kim et al. (2016) argue that the impressive performance of the TSMOM strategy constructed by Moskowitz et al. (2012) is due to the levered risk parity asset allocation method that the strategy uses. They argue that the use of time series momentum signals does not improve strategy performance. While the introduction of all costs proves detrimental to the performance of the LTSMOM strategy, there is clear evidence throughout the above analysis that applying a time-series momentum approach to the investment strategy improves performance. This is clearly visible since the 3-month LTSMOM strategy consistently performs better than the LRP portfolio. This paper therefore finds evidence that challenges the arguments of Kim et al. (2016) and elaborates on this in Section 6.5

The optimality of the 3-month lookback horizon is at ends with the empirical analysis conducted by Moskowitz et al. (2012) who find a lookback horizon of 12-months to produce the best performance. There may be several reasons behind this difference, of which the paper will discuss at greater length in Section 6.1. The above analysis shows that it is not transaction costs that inflict the most damage to the LTSMOM strategy, but rather financing costs. Indeed, accounting only for transaction costs, in the neutral case the 3-month LTSMOM strategy still provides attractive results, with a statistically significant alpha. These results challenge the findings of Lesmond et al. (2004) who argue that momentum strategies are not robust to transaction costs. Where Asness et al. (2012) discuss the various reasons for leverage aversion, this paper provides an answer from the perspective of the individual investor. The significant damage to returns caused by the high costs of financing incurred by an individual investor provide justification for leverage aversion. Of course, this paper has made assumptions regarding the cost of leverage that may be challenged. These will be discussed in Section 6.3.

The information gathered from this section of the analysis indicates that in a real-world setting, measured against the selected performance measures, the implementation of the LTSMOM and LRP strategies are not ideal. However, with much of the analysis to come, making any conclusions at this stage would be premature. Having ascertained that the main driver of performance reduction is financing costs, the outlook for the UTSMOM and URP strategies seems positive. The paper will now investigate these strategies and analyse their performance under different scenarios.

5.3 The UTSMOM and URP Strategies

The analysis of the UTSMOM and URP strategies will investigate their performance measures gross of all costs, net of transaction costs, and net of transaction costs and expense ratios. Through this analysis, the paper determines the optimal lookback horizon. The paper also determines the robustness of the strategy in the presence of transaction costs and expense ratios. Furthermore, comparing the UTSMOM strategy to the URP strategy, the paper determines whether the use of trend signals provides better performance. The analysis begins with the strategies gross of costs. Following this, the paper analyses the strategies net of transaction costs. Finally, the paper conducts the analysis of the strategies accounting for transaction costs and expense ratios.

5.3.1 The UTSMOM and URP Strategies without Costs

The performance measures for strategies gross of costs are presented in Table 5.5 and cumulative returns are displayed in Figure 5.8.

Table 5.5

Performance measures of the UTSMOM and URP Strategies without Transaction Costs

	1m	2m	3m	6m	9m	12m	URP
Average excess return	1.4%	2.1%	2.5%	2.3%	2.1%	2.0%	2.2%
Volatility	3.2%	3.3%	3.0%	3.0%	2.9%	3.1%	5.6%
Sharpe Ratio	0.44	0.63	0.84	0.77	0.72	0.64	0.40
Annualized Alpha	0.8%	1.5%	2.0%	1.7%	1.5%	1.4%	0.7%
t-Statistic	1.11	2.05	3.06	2.67	2.39	2.25	1.72
Max Drawdown	6.4%	6.8%	4.2%	4.7%	4.7%	5.0%	23.3%

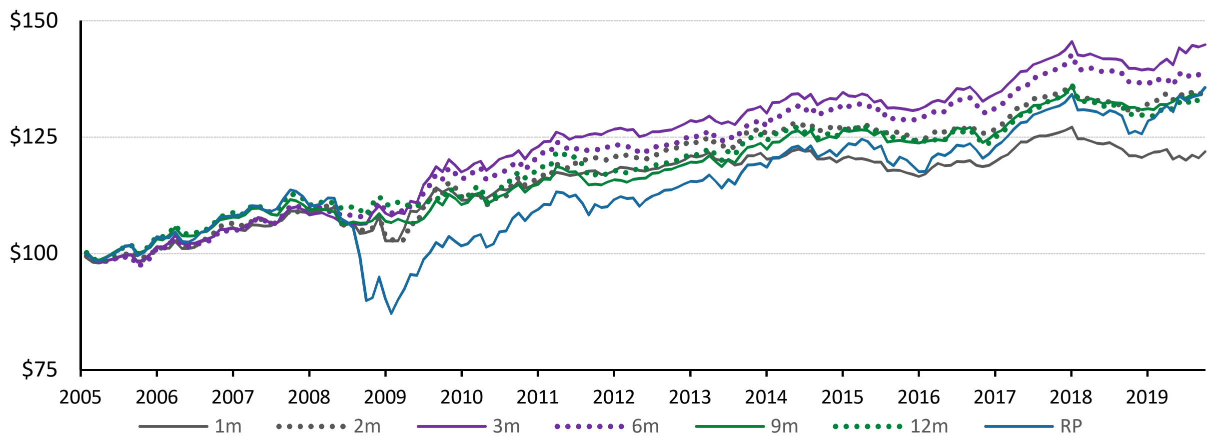


Figure 5.8 Cumulative returns of UTSMOM and URP strategies gross of costs between January 2005 and October 2019

In accordance with Asness et al. (2012), excess returns are significantly lower for the unlevered strategies compared with those of the levered portfolios. Table 5.5 shows that the highest excess return for the paper portfolios is 2.5% and is produced by the 3-month strategy. The second highest excess return is realized by the 6-month strategy at 2.3%, followed by the URP strategy which has an excess return of 2.2%. Already, a difference between the levered and unlevered portfolios is observed. The results for the levered strategies excluding costs presented in Panel A of Table 5.1 show that the LRP produces the highest excess return at 9.6%, followed by the 3-month and 9-month strategies recording excess returns of 9.0% and 8.7%, respectively. Volatilities are considerably lower for the unlevered strategies, hovering around 3% for the UTSMOM portfolios and 5.6% for the URP strategy. The 9-month strategy has the lowest volatility at 2.9%, followed by the 3-month and 6-month strategies, both with volatilities of 3%. The 3-month strategy produces the best SR at 0.84. The 6-month strategy takes second place with an SR of 0.77 and the third-best SR is achieved by the 9-month strategy. The URP strategy realizes the lowest SR at 0.4. Again, a clear difference between the dynamics of the performance measures with respect to lookback horizons between the levered and unlevered strategies is observed. Not only is the order of optimal lookback horizons different, in the unlevered case the 1-month strategy produces a higher SR than the

URP. In the levered case, the 1-month strategy provides the worst SR, whereas in the unlevered case it is the URP strategy that is inferior. Consistent in both the levered and unlevered case, however, is the superior performance of the 3-month strategy in terms of the SR.

The performance of the strategies in terms of alpha follow a very similar order as with the SR. All alphas display statistical significance except the 1-month strategy and URP strategy. The 3-month strategy has an alpha of 2.0% with a corresponding *t*-statistic of 3.06. Again, the 6-month strategy performs second-best with an alpha of 1.7% and *t*-statistic of 2.67. A pattern is certainly emerging, where a clear difference in terms of optimal lookback horizons is visible. While the 3-month strategy performs best in both the levered an unlevered case, the 6-month strategy seems to have replaced the 9-month strategy in second place. In their costless state, many of the UTSMOM strategies produce returns that are not fully explained by the CAPM theory. However, as was observed in the analysis of the LTSMOM strategies, the presence of costs may change this.

The MDD of the 3-month strategy is only 4.2% and is the lowest of all strategies. The 6-month and 9-month strategies both produce MDDs of 4.7%. The 1-month and 2-month strategies produce MDDs of 6.4% and 6.8%, respectively. The URP strategy performs worse than any UTSMOM strategy registering an MDD of 23.3%. Figure 5.8 shows that the MDD of the URP strategy occurs during the GFC, where the UTSMOM strategies are largely unaffected. As mentioned in Section 2.3, Moskowitz et al. (2012), highlight that TSMOM strategies perform very well during the GFC. As with the LTSMOM strategy, the reason that the UTSMOM strategy does not experience gains during the GFC is that the strategy does not short assets but rather excludes them from the portfolio. While the UTSMOM strategies do not realize the significant gains during the GFC that the TSMOM does, it is still shielded from the significant losses experienced by strategies that do not use signal. This is exemplified by the huge loss experienced by the URP strategy. Interestingly, while the LTSMOM strategies experience significant losses in the market corrections of 2018, the UTSMOM strategies are less vulnerable to them. This is likely due to the absence of leverage in the UTSMOM strategy. This will be discussed further in Section 6.5.

5.3.2 The UTSMOM and URP with Transaction Costs

The performance measures for the UTSMOM and URP strategies accounting for bid-ask transaction costs and a broker fee of 0.1% are shown in Table 5.6. Cumulative returns are presented in Figure 5.9.

Table 5.6

Performance of UTSMOM and URP Strategies with Bid-Ask Transaction Costs and 0.1% Broker Fee

	1m	2m	3m	6m	9m	12m	URP
Average excess return	0.7%	1.6%	2.3%	2.0%	1.9%	1.8%	2.1%
Volatility	3.2%	3.3%	3.0%	3.0%	2.9%	3.1%	5.6%
Sharpe Ratio	0.23	0.49	0.75	0.69	0.65	0.59	0.38
Annualized Alpha	0.1%	1.0%	1.7%	1.5%	1.4%	1.3%	0.7%
t-Statistic	0.16	1.41	2.67	2.31	2.10	2.00	1.53
Max Drawdown	7.0%	7.3%	4.4%	5.0%	4.8%	5.2%	23.4%

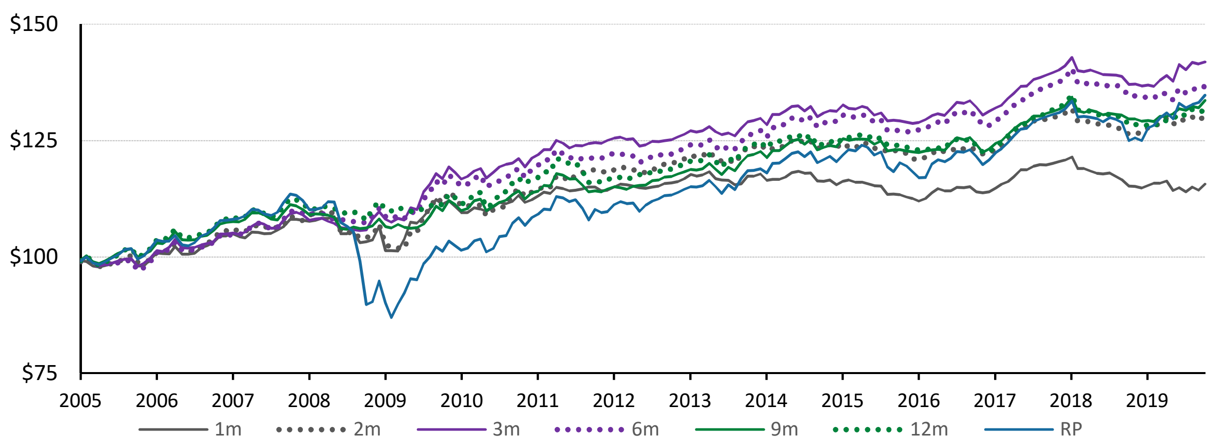


Figure 5.9 Cumulative returns of UTSMOM and URP strategies with bid-ask costs, a broker fee of 0.1%, between January 2005 and October 2019

The 3-month strategy continues to produce the best excess return at 2.3%, down by 20 bps from its costless counterpart which records an excess return of 2.5%. The 6-month strategy maintains its position as the second-best strategy with a slightly lower excess return of 2.0%, down from 2.3%, a reduction of 30 bps. The URP registers a 2.1% excess return, having dropped only 10 bps due to the incorporation of transaction costs. Volatilities remain unchanged from the paper portfolio. The 3-month strategy therefore still produces the best SR of 0.75. The 6-month strategy has an SR of 0.69, which is the second best of all strategies. Due to its higher volatility, the URP has the second-worst SR of 0.38, outperforming only the 1-month strategy, which has consistently underperformed the other strategies in almost all instances.

Accounting for transaction costs the 3-month strategy realizes an alpha of 1.7% which remains statistically significant with a *t*-statistic of 2.67. The 6-month strategy also realizes a statistically significant alpha of 1.5% with a *t*-statistic of 2.31. The 9-month and 12-month strategies also maintain statistically significant alphas. The 1-month, 2-month, and URP strategies do not realize statistically significance alphas.

Measured by MDD, the 3-month strategy also performs best, only losing 4.4% of wealth in its greatest loss of the entire period. The URP underperforms all other strategies by a large margin recording an MDD of 23.4%, which occurs during the GFC as shown in Figure 5.9. Clearly, the 3-month strategy continues to perform best, with superior performance measures in every category.

5.3.3 The UTSMOM and URP Strategies with All Costs

The performance measure for the UTSMOM and URP strategies net of transaction costs and expense ratios are shown in Table 5.7 and a graph displaying cumulative excess returns is presented in Figure 5.10.

Table 5.7

Performance measures of the UTSMOM and URP Strategies with Bid-Ask Transaction Costs, a 0.1% Broker Fee and Expense Ratios

	1m	2m	3m	6m	9m	12m	URP
Average excess return	0.6%	1.5%	2.1%	1.9%	1.8%	1.7%	1.9%
Volatility	3.2%	3.3%	3.0%	3.0%	2.9%	3.1%	5.6%
Sharpe Ratio	0.19	0.45	0.70	0.64	0.60	0.54	0.34
Annualized Alpha	0.0%	0.9%	1.6%	1.4%	1.2%	1.1%	0.4%
t-Statistic	-0.02	1.23	2.45	2.09	1.87	1.75	1.01
Max Drawdown	7.0%	7.3%	4.5%	5.0%	4.9%	5.3%	23.7%

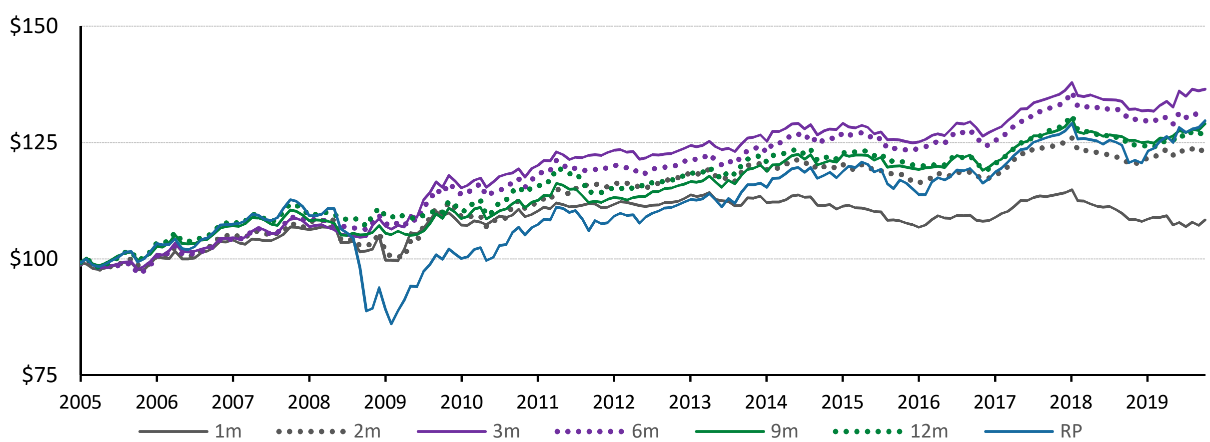


Figure 5.10 Cumulative returns of UTSMOM and URP strategies with bid-ask costs, a broker fee of 0.1% and expense ratios between January 2005 and October 2019

While slightly reducing the performance of each strategy, the inclusion of expense ratios does not change the ranking order of the strategies. The 3-month strategy continues to perform best with the highest excess return and SR. Furthermore, it realizes the highest alpha of 1.6% with a significant *t*-statistic of 2.45. Producing an MDD of 4.5%, the 3-month strategy continues to be the safest strategy in large downturns. Figure 5.10 shows that the 3-month strategy realizes the highest cumulative return at the end of the sample period. Moreover, it maintains a very stable performance throughout the entire sample period which is logical given its low volatility and MDD. In sum, accounting for transaction costs and expense ratios the 3-month strategy performs best in every category.

Concluding Remarks on the UTSMOM and URP Strategies

As with the LTSMOM strategy, the optimal lookback horizon for the UTSMOM strategy is three months. Again, this finding is different to that of Moskowitz et al. (2012) who find the 12-month lookback horizon to be optimal. Adding further nuance to the discussion of lookback horizon optimality, the UTSMOM strategy providing the second-best results is the 6-month strategy. The second-best lookback horizon for the LTSMOM strategies was identified as 9 months. These findings may be explained by the lack of clear trend signals in recent years and are discussed further in Section 6.1.

Contrary to the findings of the LTSMOM and LRP analysis, the 3-month UTSMOM strategy maintains positive results as costs are incurred on it. Lesmond et al. (2004) argue that the majority of profits gained from momentum strategies are derived from short positions which are subject to disproportionally high transaction costs rendering strategy execution unprofitable. While this may be true, accounting for transaction costs and expense ratios, the 3-month UTSMOM strategy produces an annualized alpha of 1.6% with significant *t*-statistic of 2.45. Although the magnitude of the strategy's alpha is not overwhelming, the fact that it exists and is statistically significant when accounting for transaction costs has several implications. First, it indicates that the implementation of long-only momentum strategies can be profitable, providing a new perspective to the arguments of Lesmond et al. (2004). Second, the presence of abnormal excess returns means that the CAPM does not fully explain the returns of the strategy.

The URP strategy does not realize a statistically significant alpha and underperforms the 3-month strategy against all other performance measures. The only difference between the two strategies is the use of time-series momentum signals. For this reason, it is possible to argue that the superior performance of the 3-month UTSMOM strategy compared to the URP portfolio is caused solely using time-series momentum signals. This provides insights regarding the findings of Kim et al (2016) who find that the impressive performance of the TSMOM strategy created by Moskowitz et al. (2012) derives from its asset allocation method and not its use of time series momentum signals. The paper discusses this in Section 6.5.

5.4 COMPARING INVESTMENT STRATEGIES

The optimal lookback horizons have been identified as three months for both the LTSMOM and UTSMOM strategies. Therefore, in the following subsection the terms LTSMOM and UTSMOM refer explicitly to the 3-month strategies in each case. Having determined the optimal lookback horizons and analysed their behaviour with respect to relevant costs, the paper is now primed to conduct the final part of the analysis. Here, it is the objective to determine the degree to which the LTSMOM and UTSMOM strategies outperform other standard asset allocation approaches. These benchmark strategies are the equally weighted (EW) and 60/40 portfolios. The performance measures, of each investment strategy are displayed in Table 5.8 and Figure 5.11. Panel A in Table 5.8 shows the performance measures of each strategy gross of all costs. Panel B displays the performance measures net of all costs. Figure 5.11 presents the cumulative excess returns following the same logic. To simplify the comparison of the strategies, the paper conducts a process of elimination, filtering strategies out to arrive at a conclusion.

Table 5.8

Performance measures of selected strategies. Panel A shows the measures gross of costs. Panel B shows the measures accounting for bid-ask transaction costs, a 0.1% broker fee, expense ratios and a 2.5% financing cost premium

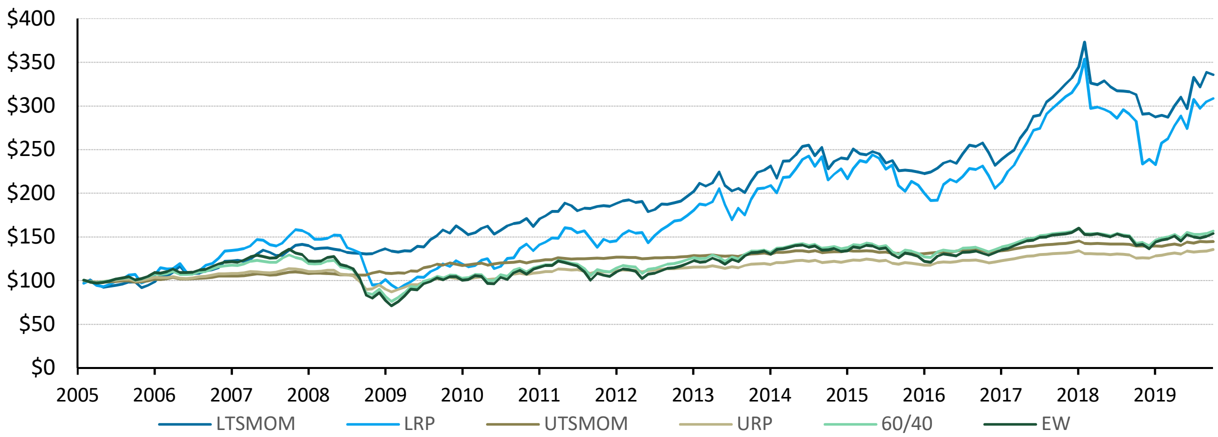
Panel A. Performance of Selected Portfolios without Costs

	LTSMOM	LRP	UTSMOM	URP	60/40	EW
Average excess return	9.0%	9.6%	2.6%	2.2%	3.6%	3.8%
Volatility	12.0%	17.8%	3.0%	5.6%	10.9%	12.8%
Sharpe Ratio	0.75	0.54	0.84	0.40	0.33	0.29
Annualized Alpha	7.1%	5.2%	2.0%	0.7%	1.0%	0.8%
t-Statistic	2.57	2.11	3.06	1.72	1.51	1.02
Max Drawdown	23.0%	43.0%	4.2%	23.3%	41.2%	47.7%

Panel B. Performance of Selected Portfolios with All Costs

	LTSMOM	LRP	UTSMOM	URP	60/40	EW
Average excess return	2.6%	0.3%	2.1%	1.9%	3.3%	3.4%
Volatility	12.1%	17.8%	3.0%	5.6%	10.9%	12.8%
Sharpe Ratio	0.22	0.02	0.70	0.34	0.30	0.26
Annualized Alpha	0.7%	-4.1%	1.6%	0.4%	0.7%	0.4%
t-Statistic	0.25	-1.62	2.45	1.01	0.98	0.52
Max Drawdown	26.5%	47.8%	4.5%	23.7%	41.5%	48.0%

Panel A



Panel B

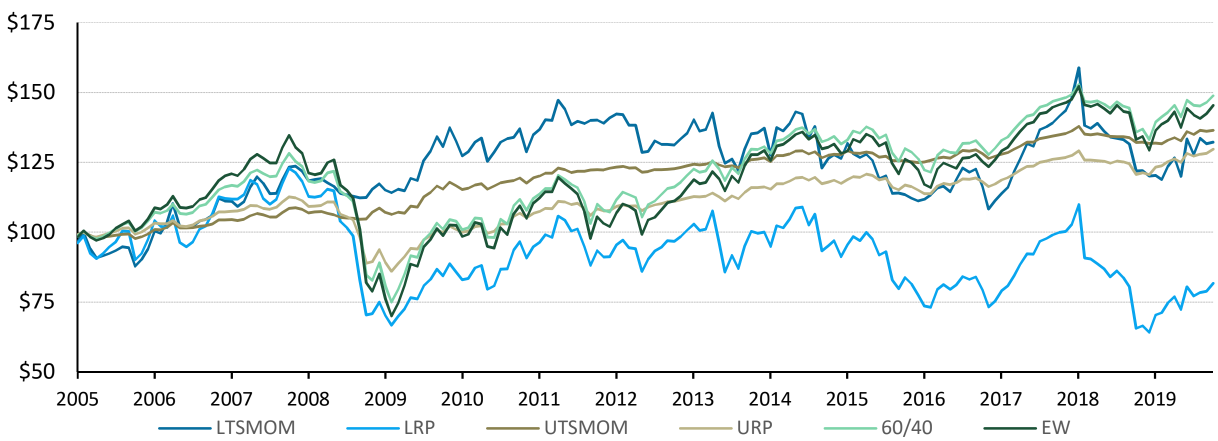


Figure 5.11 Cumulative returns of selected strategies between January 2005 and October 2019. Panel A displays the cumulative returns gross of costs. Panel B shows the cumulative returns with bid-ask costs, a broker fee of 0.1% and expense ratios.

Comparing Panel A and B in Table 5.8 and Figure 5.11, it is clear that the inclusion of costs associated with the implementation of the selected strategies has a negative impact on their performance. This is most starkly emphasized by the difference in the performance of the levered strategies in their paper form as opposed to their performance when accounting for costs. As discussed in Section 5.2, the majority of this decline in performance is caused by the financing costs associated with using leverage. Panel A in Figure 5.11 shows the cumulative returns of the levered portfolios towering above the other strategies, both ending the sample period having more than tripled their wealth. However, as Panel B from the same figure shows, this dominance is not present when accounting for the costs associated with strategy execution. The performance of the LTSMOM strategy aligns more closely with the unlevered strategies and the LRP strategy significantly underperforms them realizing a negative cumulative return at the end of the sample period.

Accounting for costs, the LRP strategy produces the worst performance of all strategies, barely realizing a positive excess return at 0.3% and producing the highest volatility at 17.8%. The remaining performance measures are also highly undesirable. With the obvious underperformance of this strategy, it makes little sense to provide an in-depth comparison of its performance with the other strategies. The LRP strategy is therefore exempt from further analysis and is deemed to be unimplementable in the current setting. The remaining five portfolios, however, are more closely aligned in their performance and require further analysis.

The EW strategy displays the highest mean excess return of all strategies at 3.4%, closely followed by the 60/40 strategy which achieves an excess return of 3.3%, a difference of 10 bps. While the EW outperforms the 60/40 portfolio with respect to excess returns, it is inferior in all other aspects. The 60/40 strategy has a lower volatility of 10.9% compared to the EW strategy which has a standard deviation of 12.8%. This results in the 60/40 strategy realizing a higher SR than the EW strategy at 0.3 and 0.26, respectively. Therefore, the 60/40 strategy has a better risk-adjusted return than the EW portfolio. Neither the 60/40 nor the EW portfolio realize statistically significant alphas. The 60/40 strategy has a lower MDD than the EW portfolio at 41.5% and 48.0%, respectively. Observing Figure 5.11, it is clear that the MDD takes place during the GFC, as would be expected. It could be argued that the 60/40 strategy will likely perform better than the EW strategy in severe market downturns. Of course, a future crisis may have different underlying mechanisms that render a clear conclusion on this subject difficult. Nonetheless, given the small difference in excess returns between the two strategies and the otherwise superior performance of the 60/40 strategy it seems reasonable to remove the EW strategy from further analysis and use the 60/40 strategy for comparison with the remaining strategies.

Panel B in Table 5.8 clearly shows that the UTSMOM strategy outperforms the URP strategy in every category. The URP strategy could therefore also be removed. However, prior to this it is important to note that the URP strategy outperforms the 60/40 strategy in several ways. In fact, the 60/40 portfolio only outperforms the URP strategy in terms of excess returns and alphas which are not statistically significant in either case. The far lower volatility of the URP strategy at 5.6% compared to the 10.8% displayed by the 60/40 strategy results in the URP strategy obtaining a higher SR. These are 0.34 and 0.30 for the URP and 60/40 strategies, respectively. The MDD of the URP is only 23.7% compared to 41.5% for the 60/40 strategy. Figure 5.11 indicates that the MDD for the URP also occurs during the GFC as was found for the 60/40 strategy. The URP strategy therefore appears to be far more resilient to significant market downturns than the 60/40 strategy. Again, this finding must be viewed with caution given the infinite causes of crises. Nevertheless, in this case, the URP strategy outperforms the 60/40 portfolio. The URP strategy is certainly not outperformed by the 60/40 strategy. However, the larger excess return realized by the latter and the fact that the URP is outperformed by the UTSMOM strategy in every measurement category means that the paper excludes the URP strategy from further analysis.

Having simplified the analysis be removing the LRP, EW and URP strategies from further consideration, three strategies remain. The remaining strategies that must be compared are the LTSMOM, UTSMOM and 60/40 strategies. The 60/40 strategy outperforms the LTSMOM strategy in all categories except for MDD. The LTSMOM has an excess return that is 70 bps lower than the 60/40 strategy at 2.6% while simultaneously recording a volatility of 12.1%, 20 bps higher than the 60/40 strategy. The LTSMOM strategy therefore realizes an SR of only 0.22, lower than the 60/40 strategy which has an SR of 0.30. This indicates that in more normal market conditions, the 60/40 strategy is superior, however, in the event of a serious market downturn an investor would be better positioned carrying the LTSMOM strategy. Viewing Figure 5.11, it is clear that the LTSMOM strategy is largely unaffected by the market turmoil of the GFC which is, of course, a desirable attribute. However, the strategy is punished more harshly during the market corrections of 2018 than the 60/40 strategy (Fisher, 2019). The determination of which of these two strategies is optimal therefore depends very much on investor preferences.

The UTSMOM strategy outperforms both the 60/40 and LTSMOM strategies in every category besides excess return where it registers a lower value in both cases. Producing an excess return of 2.1%, the UTSMOM strategy falls short of the LTSMOM and 60/40 strategies by 50 bps and 120 bps, respectively. However, the remaining performance measures of the UTSMOM strategy display overwhelming superiority when viewed in contrast to the 60/40 and LTSMOM strategies. Boasting an annualized volatility of only 3%, the UTSMOM strategy exhibits an SR of 0.7. This is over three times greater than the SR of the LTSMOM strategy and more than double that of the 60/40 strategy, with SRs of 0.22 and 0.30, respectively. Adding to the attractiveness of the UTSMOM strategy is its realization of an annualized alpha of 1.6% with a statistically significant t-statistic of 2.45. The UTSMOM strategy both possesses the highest alpha and is the only portfolio where this measure is statistically significant. In terms of MDD, the UTSMOM also outperforms all strategies by a high margin. The UTSMOM records an MDD of only 4.5% whereas the LTSMOM and 60/40 strategies have MDDs of 23.0% and 41.2%, respectively. Viewed in conjunction with Figure 5.11 it is clear that the UTSMOM strategy is by far the most stable, neither losing much wealth during the GFC nor the multiple corrections of 2018.

Speaking of rationality, it seems highly irrational that any investor would opt to hold the 60/40 portfolio or LTSMOM portfolio, despite their higher excess returns, given the risk-adjusted returns and stable performance they could achieve by holding the UTSMOM portfolio. However, as the saying goes, *you can't eat risk-adjusted returns.* Evidence has been found that the application of leverage with the purpose of increasing returns may prove difficult, given the financing costs an individual investor could expect to be subjected to. Therefore, it is likely that in order to increase returns, other measures must be taken. This will be discussed in more detail in Section 6.6.

6 DISCUSSION AND CONCLUSION

This section of the paper discusses the most significant findings from the analysis with the aim of providing a broad and nuanced account of what has been uncovered. As mentioned in the introduction, the paper answers the research question by answering six smaller questions. The paper provides answers to these questions in this section of the paper. Section 6.1 discusses the existence of price continuation and the optimal lookback horizon, concluding with an answer to Question 1 of the paper. The paper discusses the impact of transaction costs on the performance of the time-series momentum strategies in Section 6.2 and provides an answer to Question 2. Section 6.3 discusses the impact of financing costs on the performance of the LTSMOM strategy and answers Question 3. The paper discusses the impact of expense ratio costs, specific to ETFs, on strategy performance and answers Question 4 in Section 6.4. Following this, Section 6.5 discusses whether using time series momentum signals improves strategy performance and answers Question 5. Finally, the paper discusses whether the developed long-only time series momentum perform better than other standard asset allocation methods and concludes by answering question 6.

6.1 PRICE CONTINUATION AND THE OPTIMAL LOOKBACK-HORIZON

Hurst et al. (2017) argue that clear trends have not been present in recent years, highlighting that the current economic environment has not been optimal for trend-following strategies. The presence of trends is essential for a time series momentum strategy. Therefore, the paper tests for price continuation in the data. Considering the change in trend dynamics, the paper also analyses the performance of strategies using different lookback horizon to identify which of these produces the best performance measures.

The pooled panel autoregression performed in Section 4.1 reveals statistically significant price continuation in the data. The structure of this continuation is, however, quite different from that found by Moskowitz et al. (2012). In the regression performed in this paper, only the first six lags produce positive t-statistics, of which four are statistically significant. Noticeably, the first lag does not produce a statistically significant t-statistic. After the sixth lag, the t-statistics begin to oscillate, almost randomly, between positive and negative values. Tested on all asset classes, Moskowitz et al. (2012) find positive t-statistics for each of the first eleven lags, seven of which are statistically significant. Moreover, negative t-statistics are found from the twelfth to the nineteenth lag, of which two are statistically significant. These results portray a clear picture of trend and trend reversal dynamics, which is not as visible in this paper's results. Furthermore, the paper finds the optimal lookback-horizon to be 3-months. Moskowitz et al. (2012), on the other hand, find strong evidence that the lookback horizon providing the best performance, measured by alpha, is 12 months. Several factors may cause this difference.

First, the asset classes under consideration are different. Moskowitz et al. (2012) analyse time-series momentum using futures contracts, where this paper investigates ETFs. While this may have some influence on the results, the underlying assets are quite similar in the two studies and for this reason it seems unlikely that this would have a strong impact on the results.

Second, Moskowitz et al. (2012) investigate long-short strategies, whereas this paper focuses on long-only strategies. To gain insight into whether this has had an impact on the optimal lookback horizon performance measures have been calculated for a long-short TSMOM strategy without transaction costs following the methodology of Moskowitz et al. (2012) and can be seen in Appendix B. The long-short strategies display a very similar pattern to that observed in the LTSMOM strategy with the 3-month strategy producing the best overall performance measures. Therefore, it seems reasonable to argue that the difference in the optimal lookback horizon is not because this paper analyses long-only portfolios.

Finally, the argument of Hurst et al. (2017) that clear trends have not been present in recent years could influence the results. Since the study performed by Moskowitz et al. (2012) is conducted on data from January 1965 to December 2009, whereas this paper analyses more recent data ranging between January 2004 and October 2019, it seems likely that this explains some of the difference in results.

Evidence from the transaction cost sensitivity analysis performed in Section 5.2.2 indicates that as transaction costs increase, the optimality of the lookback horizon shifts. Panel C in Table 5.2 presented in Section 5.2.2 shows that when transaction costs are high, the 12-month strategy performs best. In fact, in this scenario the 3-month strategy is outperformed by the 9-month strategy and even the LRP strategy. This makes sense since, as highlighted by Pedersen (2015), transaction costs are higher for strategies that use short-term trend signals than long-term signals. The reason for this is that the short-term trends will switch between 0 and 1 more often because the impact of one month's performance will have a greater impact on the mean excess return used to determine $sign(r^{s}_{t-h,t})$ than on long-term trends. The change in the signal results in a larger transaction size since all holdings in this asset must be either bought or sold, compared to a smaller incremental change in asset holdings associated the signal remaining unchanged. The effects of this should be smaller for the long only strategies considered in this paper compared to the long-short TSMOM strategy considered in the studies of Moskowitz et al. (2012) and Pedersen (2015). The reason for this is that as the signal changes in the LTSMOM and UTSMOM strategies, assets will either be bought or sold to or from a position of zero. The TSMOM strategy, on the other hand, will either buy or sell beyond zero, resulting in a far larger transaction size. This implies that transaction costs should be inherently smaller in the long-only strategies compared with the long-short TSMOM strategy.

6.1.1 Answer to Question 1

There is evidence of return continuation in the data, however, the structure of this continuation is different to that seen in the study performed by Moskowitz et al (2012), displaying less pronounced price continuation. Moreover, the paper finds the optimal lookback horizon in the data to be 3-months for both the LTSMOM and UTSMOM strategies. This also differs from the findings of Moskowitz et al. (2012) who find a 12-month lookback horizon to be provide the best results. The paper argues that the differences may be caused by a lack of clear trends in recent years causing the dynamics of the strategy to change. Finally, the paper finds that as transaction costs increase, strategies using longer lookback horizons perform best. These findings are supported by theory and add further depth to understanding of the optimal lookback horizon. Not only must an investor be aware that the optimal lookback horizon may vary across assets and time, he must consider that it will transform depending on the size of transaction costs. This emphasizes the need to integrate transaction costs into back-testing procedures prior to determining lookback horizons since they change the very composition of the strategy.

6.2 The Impact of Transaction Costs on the LTSMOM and UTSMOM Strategies

When implementing a strategy in real life an individual investor is subject to transactions costs. Therefore, the paper conducts a comprehensive study to determine the degree to which the LTSMOM and UTSMOM strategies are robust to transaction costs. Having identified the 3-month lookback horizon as optimal in the data for both the LTSMOM and UTSMOM strategies, the remainder of the paper will discuss the performance of these strategies only, unless specifically stated otherwise. For simplicity, these are referred to as the LTSMOM and UTSMOM strategies from here on. The results from Section 4.2 of the paper show that both the LTSMOM and UTSMOM strategies produce attractive performance measures gross of costs.

The transaction cost sensitivity analysis of the LTSMOM strategy shows that in the neutral case with bid-ask transaction costs and a broker fee of 0.1% of transaction size, the strategy produces a statistically significant annualized alpha of 5.9%. Furthermore, under these conditions the strategy realizes an average excess return of 7.8% and an SR of 0.65. However, in the pessimistic case where broker costs are set to 0.5% of transaction size, performance is significantly reduced. In this case, the annualized alpha of the LTSMOM strategy is only 1.6% and is not statistically significant. Moreover, the excess return is reduced to 3.5% and the SR is 0.29.

With bid-ask transaction costs and a broker fee of 0.1% of transaction size, the UTSMOM strategy also produces positive results. The strategy realizes a statistically significant annualized alpha of 1.7%, an excess return of 2.3% and an SR of 0.75. The paper does not report a sensitivity analysis of the UTSMOM strategy in the main text, however, the results of this analysis can be found in Appendix A. These show a similar pattern to the LTSMOM strategy.

These results challenge the findings of Lesmond et al. (2004) who argue that transaction costs render the execution of momentum strategies unprofitable. While the results of the analysis provide a positive outlook for the implementation of the time series momentum strategies, there is a caveat to the findings. Specifically, this paper using the method prescribed by Corwin and Schultz (2012) to estimate bid-ask spreads using daily high and low prices. If the modelled bid-ask spreads have underestimated the true costs of trading, then strategy performance will have been overestimated. If the true transaction costs resemble the pessimistic case, then the strategies would not be robust to these costs. Nonetheless, under the assumption that these costs are estimated correctly and that a broker fee of 0.1% is obtainable, the paper finds both strategies to be robust to trading costs.

6.2.1 Answer to Question 2

Based on data retrieved from online brokers, the paper assumes a broker fee of 0.1% to be obtainable in the real world. Therefore, the paper finds that both the LTSMOM and UTSMOM strategies are robust to the transaction costs an individual investor is subject to. However, the paper has also found evidence that higher transaction costs can significantly reduce strategy performance, emphasizing the importance of monitoring transaction costs closely and seeking the lowest possible broker fee available.

6.3 THE IMPACT OF FINANCING COSTS ON THE LTSMOM STRATEGY

When using leverage an individual investor will be subject to financing costs. For this reason, the paper conducts a financing cost sensitivity analysis of the LTSMOM strategy to determine whether it is robust to these costs. The LTSMOM strategy displays promising results, both excluding costs and including transaction costs. The positive performance of the LTSMOM strategy is, however, greatly depleted in the presence of financing costs. As shown in Section 5.4, accounting for financing costs, the LTSMOM strategy is outperformed by all other strategies except the LRP portfolio which is also subject to financing costs. These results provide some insights relevant to the leverage aversion theory presented by Asness et al. (2012). The authors highlight the investment benefits that can be obtained by exploiting the empirically flat SML by concentrating weight in safer assets and applying leverage to the portfolio. They explain that leverage aversion may be caused by an inability or unwillingness to make use of leverage. In this case, it seems that an inability to gain access to cheap leverage should cause an investor to be unwilling to apply leverage to the portfolio. Certainly, at the interest rates that have been observed from online brokers it seems reasonable to argue that the cost of leverage is simply too high to expect any gains from its application to the LTSMOM strategies. In fact, the results from the sensitivity analysis show that even in the *optimistic* scenario, where the annualized interest rate premium over the risk-free rate is set to 1%, the prospects are not encouraging.

While the evidence suggests that it is not optimal for an individual investor to implement the LTSMOM strategy in real life, there are several elements that have led to this conclusion that must be discussed. First, it has been assumed that an individual investor would reasonably be able to borrow at the risk-free rate plus an annualized premium of 2.5%. Second, the way in which the LTSMOM strategy has been constructed may cause it to perform worse than could be the case. The paper will now discuss these points.

The assumed interest rate that an individual investor is subject to when borrowing is determined based on readily available information on a range of online trading platforms. However, it is within reason to argue that if an investor establishes a long-term relationship with a broker, he may be able to negotiate more favourable borrowing terms. Moreover, it is possible that an individual who invests large sums of wealth may also be able to obtain a lower borrowing rate. As mentioned in Section 3.1.2, Interactive Brokers offer cheaper rates to customers who qualify for a PRO membership, which indicates that such scenarios are feasible. With that said, the sensitivity analysis shows that even at an annualized financing cost premium of 1%, the LTSMOM fails to produce a statistically significant alpha. It does, however, obtain an annualized excess return of 6%, an SR of 0.5 and an MDD of only 24.3%. This implies that financing costs must be lower than 1% for the LTSMOM strategy to realize a statistically significant alpha. Of course, this may be different for an alternative set of assets and will likely vary with time. Therefore, there is no prescriptive interest rate that will ensure the positive performance of the LTSMOM strategy.

Finally, the way in which the LTSMOM strategy is constructed, accounting for financing costs may lead to unnecessarily poor performance. The root of this problem lies in the way the excess returns have been calculated and used to determine the $sign(r^s_{t-h,t})$ component of the LTSMOM strategy. Specifically, excess returns used to determine whether $sign(r^s_{t-h,t})$ is equal to 0 or 1 are calculated by subtracting the risk-free rate from the return of the instrument *s*. However, since the financing cost is the risk-free rate plus a premium and is applied to the LTSMOM formula after the calculation of $sign(r^s_{t-h,t}$ assets are included in the portfolio that may never have a positive excess return due to the higher financing cost. This information could be integrated in the calculation of $sign(r^s_{t-h,t})$ and could possibly have a positive effect on the performance of the LTSMOM strategy.

6.3.1 Answer to Question 3

Based on the results obtained in the analysis and the above discussion, the paper concludes that the LTSMOM strategy is not robust to the financing costs an individual investor is subject to. The LTSMOM is outperformed by every other strategy besides the LRP strategy. However, an alteration in the construction of the LTSMOM strategy, integrating financing costs into the calculation of the signal, may provide better results. Furthermore, if an investor can gain access to a much lower financing cost than has been used in this paper, it is possible that strategy can produce attractive results.

6.4 USING ETFS IN TIME SERIES MOMENTUM STRATEGIES

The assets analysed in this paper are ETFs which require investors to pay fees known as expense ratios. With the purpose of conducting an analysis that resembles real-life strategy implementation as much as possible, the paper investigates whether the strategies are robust to expense ratio costs.

For the LTSMOM strategy the ERs are first included in the calculation of returns after accounting for transaction and financing costs. While the performance of the LTSMOM strategy is severely undermined by the presence of financing costs, it is still possible to observe the impact of the ERs. The excess return of the LTSMOM strategy is reduced by 60 bps and volatility remains constant. This results in a decline of the SR from 0.27 to 0.22. The MDD also increases slightly. While the performance of the strategy is reduced, the effects are greater for the LRP strategy. The excess return of the LRP strategy is reduced by 90 bps and its SR falls from 0.07 to 0.02. As with financing costs, these results are logical. With the LRP constantly invested in all assets throughout the sample period it is subject to higher ER costs than the LTSMOM strategy. The impact of the ERs is far more subdued for the UTSMOM strategy which loses only 20 bps in excess return. The LRP also drops 20 bps. Furthermore, the UTSMOM realizes a statistically significant alpha of 1.6%. This finding challenges the assumptions of the Efficient Market Hypothesis, which states that prices reflect all currently available information. Given its risk, this strategy realizes a higher excess return than can be explained by the CAPM. The paper, therefore considers the UTSMOM strategy to be robust to ERs.

While the performance measures of the strategies are reduced by ERs, the effects are small. Of course, futures contracts do not bear these costs at all, however, the necessary rolling of the contracts increases the complexity of the strategy. Although stocks are not subject to expense ratios and are not complicated, they possess other characteristics that are undesirable. Specifically, stocks are subject to idiosyncratic risk, which renders them prone to sharp adjustments in price. As highlighted by Moskowitz et al. (2012) the TSMOM strategy underperforms during sharp trend reversal. ETFs on the other hand, are highly diversified which according to Markowitz (1959) reduces their overall risk. Therefore, it could be argued that the relatively small impact on performance is a small price to pay for the diversification benefits provided by the ETFs.

6.4.1 Answer to Question 4

The paper concludes that the UTSMOM strategy is robust to expense ratio costs. The paper is unable to provide a clear conclusion with respect to the LTSMOM strategy, due to its poor performance prior to the inclusion of expense ratios. Considering, the diversification benefits that ETFs possess and the positive performance of the UTSMOM strategy, it seems within reason to argue that this asset class is appropriate for use in time series momentum strategies.

6.5 THE BENEFITS OF TIME SERIES MOMENTUM

Moskowitz et al. (2012) find that their TSMOM strategy produces superior returns compared to a long only strategy where $sign(r_{t-12,t}^{s})$ is set to one. These results are obtained by performing a regression where the only reported performance measure is alpha. Kim et al. (2016), on the other hand, argue that the results obtained by Moskowitz et al. (2012) are caused by using volatility scaling and leverage. Therefore, this paper analyses a broad set of performance measures to investigate whether the use of time-series momentum truly improves strategy performance.

Throughout the analysis the paper compares the performance measures of the long-only TSMOM strategies with their all-long counterparts where $sign(r_{t-h,t}^{s})$ is permanently set to one. The results enable the paper to gain a deeper understanding of the dynamics of each strategy which will now be discussed. As in Section 6.2, the LTSMOM and UTSMOM strategies refer to the 3-month lookback horizon versions of each strategy.

In most instances, the LTSMOM strategy produces superior performance measures compared to the LRP strategy. Gross of costs, the LTSMOM produces better performance measures in every category besides excess return. The same is true when accounting for transaction costs in the optimistic and neutral cases where broker fees are 0.05% and 1%, respectively. Cumulative returns graphs show that the LTSMOM strategy is well shielded from the losses of the GFC in all scenarios, whereas the LRP strategy realizes significant losses during the crisis. Only under the transaction cost sensitivity analysis, in the pessimistic case where the broker fee is 0.5% does the LRP produce a higher SR than the LTSMOM strategy. However, in this case, the LRP strategy still produces a far higher MDD and volatility than the LTSMOM strategy. Accounting for financing costs, the LTSMOM strategy fails to perform well. However, view comparatively, the LTSMOM strategy is more robust to financing costs than the LRP strategy. This is not surprising, since, as defined in Section 2.4, the LTSMOM strategy uses the wealth that would have been allocated to inactive assets to reduce the overall use of external financing. The LRP strategy, being passively long, is therefore far more reliant on external financing, increasing the related costs. Therefore, the paper argues that the use of signals in this case does facilitate better performance.

The results from the analysis of the unlevered strategies show that the UTSMOM strategy outperforms the URP strategy in every measurement category, both gross and net of costs. Accounting for all costs, the UTSMOM produces an SR that is more than double as large as the URP strategy. In this case the UTSMOM strategy produces a statistically significant alpha, which the URP does not. Moreover, the UTSMOM strategy records an MDD of 4.5% while the URP strategy has an MDD of 23.7%. Since the only difference between the two strategies is the use of time series signals, it is clear that these are the driving force behind the better performance of the UTSMOM strategy.

6.5.1 Answer to Question 5

Given the costs associated with the real-life implementation of the LTSMOM and UTSMOM strategies, the paper concludes that both strategies perform over and above their all-long, otherwise identical, counterpart strategies. This finding supports the results obtained by Moskowitz et al. (2012) and challenges those of Kim et al. (2016).

6.6 The Superior Performance of the UTSMOM Strategy

The paper compares the created strategies with a 60/40 and equally weighted (EW) strategy to determine whether the they are worth implementing. The analysis in Section 5.4 finds that accounting for all costs, the UTSMOM strategy is the only one to realize a statistically significant alpha. Moreover, it has the highest SR and produces excellent risk measures, both in terms of volatility and MDD. Only in terms of excess returns is the strategy outperformed. Despite producing a lower excess return, the paper judges that the UTSMOM strategy outperforms every other strategy based on its overall performance. Nonetheless, the low excess return produced by the strategy warrants further discussion. This paper finds evidence that the financing costs incurred by an individual investor associated with the leverage used in the LTSMOM strategy strongly depletes its performance, rendering it suboptimal to execute. Therefore, the method advocated by Asness et al. (2012) of applying leverage to safer assets to increase returns is arguably difficult to implement for an individual investor. Hence, to realize higher returns another approach much be used.

Hurst et al. (2017) argue that time series momentum strategies can provide hedging benefits when combined with a 60/40 strategy. As depicted in Figure 5.11 the UTSMOM strategy provides very stable returns throughout the entire sample period, both during the GFC and in sharp trend reversals. However, contrary to the long-short TSMOM strategy, the UTSMOM strategy does not produce strong returns during crises since it does not profit from market downturns. Therefore, the UTSMOM strategy is not a suitable hedging instrument as such. While the strategy may not hedge risk, it certainly can reduce it. Combining a UTSMOM portfolio with a riskier portfolio exhibiting higher expected returns is a way to increase returns while still benefiting from the strengths of the strategy.

Another way to utilize the benefits of the UTSMOM strategy without using leverage is to combine the time-series momentum principals with an asset allocation method other than risk parity. Since evidence has been found that the UTSMOM produces performance measures above and beyond those achieved by the URP strategy, it seems reasonable to assume that the same is possible for the EW portfolio, the 60/40 portfolio, or another portfolio entirely. As shown in Panel B of Table 5.8, both the 60/40 and EW strategies realize higher excess returns than the URP strategy. Of course, these higher returns are associated with greater risk compared to the URP strategy as measured by volatility and MDD. Nonetheless, for an investor willing to make this trade-off, this provides a way in which returns can be increased while taking advantage of the benefits produced by using time-series momentum signals.

Finally, a simple alteration can be made to the UTSMOM formula, that could result in higher excess returns. As was discussed in Section 2.4, portfolio weights are calculated ignoring the $sign(r^s_{t-k,t})$ component resulting in the weight $\sigma^{-1}_{t,s}/\sum_i \sigma^{-1}_{t,s}$ for each asset *s,* regardless of the signal. This means that wealth not allocated to an asset due to $sign(r^s_{t-k,t})$ being equal to zero, will instead be allocated to the risk-free rate. As mentioned, the inclusion of the signal results in the weight $\sigma^{-1}_{t,s}/\sum_i sign(r^s_{t-h,t})\sigma^{-1}_{t,s}$ for each asset *s,* which could cause overly high concentrations in few assets. The more assets with zero signals, the more concentrated the portfolio would become. Of course, alternative methods exist whereby less weight could be allocated to the risk-free rate enabling greater excess returns without allocating too much weight to one asset. For instance, a maximum weight allocated to each asset could be imposed such that a modified version of Equation 2.14 could be used. This would result in the formula:

$$r^{TSMOM}_{t,t+1} = \sum_{s=1}^{S_t} \left(sign(r^s_{t-k,t}) \min\left(\frac{\sigma^{-1}_{t,s}}{\sum_i sign(r^s_{t-k,t})\sigma^{-1}_{t,s}}, MW \right) r^s_{t,t+1} \right) - TC_{t+1} \ , \tag{6.1}$$

Where *MW* denotes maximum asset weight, which could be set at a desired level, 10% for instance. The function $\min\left(\frac{\sigma^{-1}_{t,s}}{\sum_i sign(r^s_{t-h,t})\sigma^{-1}_{t,s}}, MW\right)$, would in this case restrict the allocation of weight to a maximum level of 10%. This alteration of the UTSMOM formula could arguably facilitate higher excess returns, since less wealth would be allocated to the risk-free asset. Intuitively, this would with great likelihood cause the portfolio to be riskier, with volatility and MDD increasing. The UTSMOM formula can be manipulated in many ways that presents a great deal of flexibility regarding how an investor can implement the strategy.

6.6.1 Answer to Question 6

Accounting for all costs, the paper finds that the UTSMOM strategy produces the best all-round performance of all the considered strategies, by a large margin. The LTSMOM strategy, on the other hand, does not outperform other standard asset allocation strategies, largely due to the financing costs associated with strategy execution. Therefore, the paper concludes that an individual investor can realize superior portfolio performance compared to traditional asset allocation strategies by implementing the UTSMOM strategy.

While the UTSMOM strategy does possess desirable investment characteristics, its low excess return renders the strategy more suitable to risk-averse investors. With leverage deemed too expensive other methods must be used to increase returns. Changing the way in which the strategy is constructed may provide higher excess returns, at the expense of increasing risk. Combining the UTSMOM strategy with a riskier portfolio displaying higher expected returns would likely have a similar effect. Finally, applying time-series momentum signals to an asset allocation method other than risk parity may also result in higher excess returns, again at the expense of increasing risk.

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APPENDICES

Appendix A

Table A1

Performance measures of the UTSMOM strategies with different lookback horizons and the URP strategy with bid-ask transaction costs and varying broker fees. Panel A shows the performance measures with a 0.05% broker fee. Panel B shows the measures with a 0.1% broker fee. Panel C uses a broker fee of 0.5%.

Panel A: 0.05% Broker Fee

	1m	2m	3m	6m	9m	12m	URP
Average excess return	1.0%	1.8%	2.4%	2.2%	2.0%	1.9%	2.2%
Volatility	3.2%	3.3%	3.0%	3.0%	2.9%	3.1%	5.6%
Sharpe Ratio	0.32	0.56	0.79	0.72	0.68	0.61	0.39
Annualized Alpha	0.4%	1.2%	1.9%	1.6%	1.5%	1.3%	0.7%
t-Statistic	0.60	1.71	2.85	2.48	2.23	2.11	1.62
Max Drawdown	6.7%	7.1%	4.3%	4.8%	4.8%	5.1%	23.4%

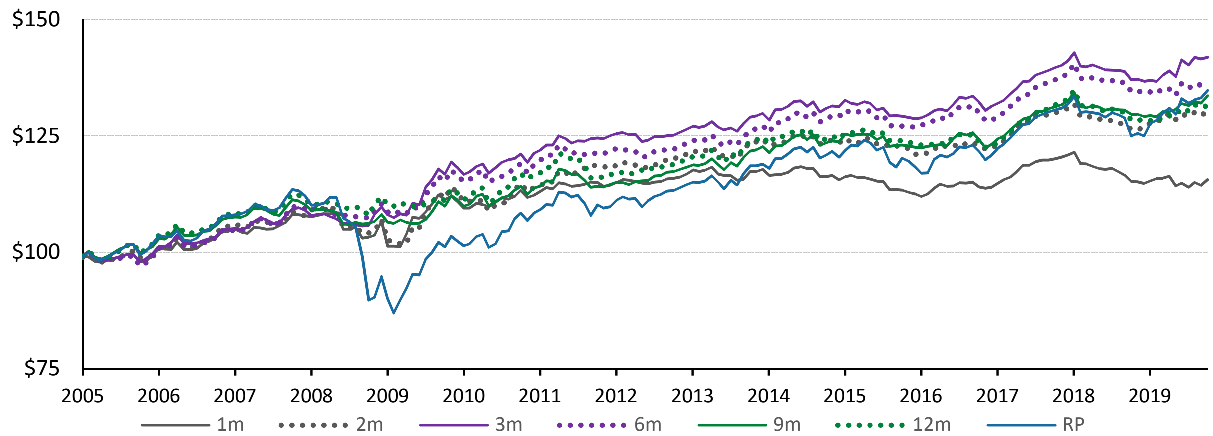
Panel B: 0.1% Broker Fee

	1m	2m	3m	6m	9m	12m	URP
Average excess return	0.7%	1.6%	2.3%	2.0%	1.9%	1.8%	2.1%
Volatility	3.2%	3.3%	3.0%	3.0%	2.9%	3.1%	5.6%
Sharpe Ratio	0.23	0.49	0.75	0.69	0.65	0.59	0.38
Annualized Alpha	0.1%	1.0%	1.7%	1.5%	1.4%	1.3%	0.7%
t-Statistic	0.16	1.41	2.67	2.31	2.10	2.00	1.53
Max Drawdown	7.0%	7.3%	4.4%	5.0%	4.8%	5.2%	23.4%

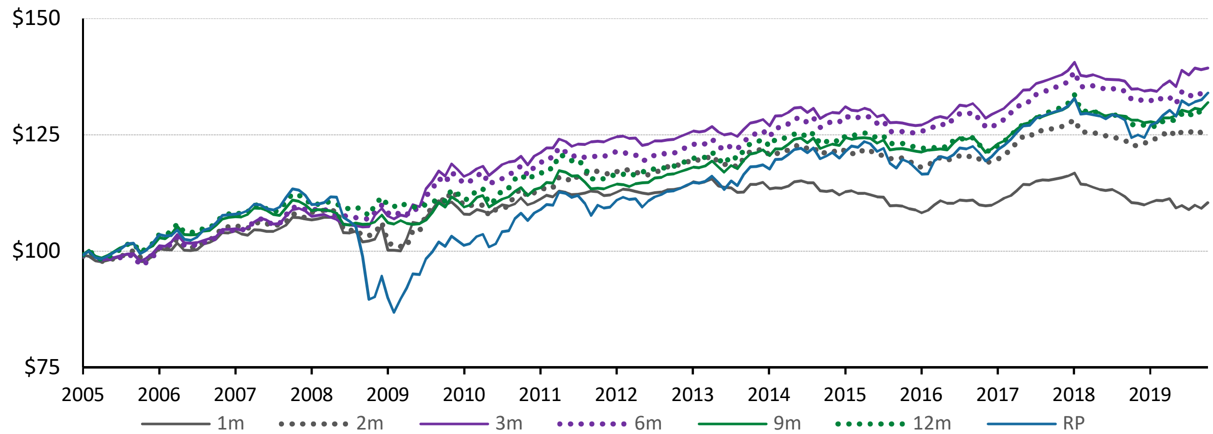
Panel C: 0.5% Broker Fee

	1m	2m	3m	6m	9m	12m	URP
Average excess return	-1.8%	0.0%	1.3%	1.2%	1.2%	1.2%	1.8%
Volatility	3.3%	3.4%	3.1%	3.0%	2.9%	3.1%	5.6%
Sharpe Ratio	-0.53	-0.01	0.43	0.39	0.42	0.40	0.33
Annualized Alpha	-2.4%	-0.6%	0.8%	0.7%	0.7%	0.7%	0.4%
t-Statistic	-3.06	-0.84	1.21	0.99	1.07	1.08	0.88
Max Drawdown	24.8%	9.2%	5.2%	6.0%	5.5%	5.9%	23.8%

Panel A



Panel B



Panel C

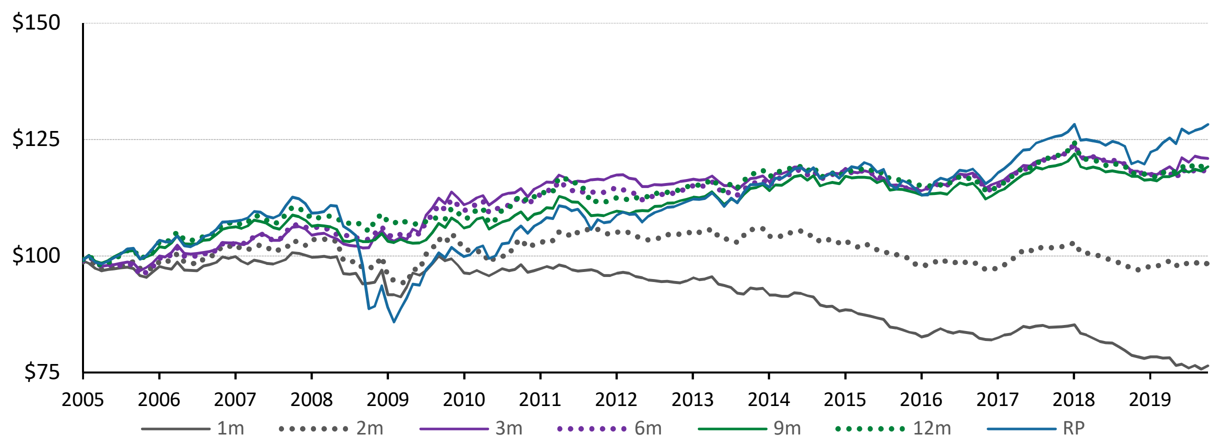


Figure A1 Cumulative excess returns of the UTSMOM and URP strategies. Panel A shows the performance with bid-ask transaction costs and a 0.05% broker fee. Panel B shows the performance with bid-ask transaction costs and a 0.1% broker fee. Panel C shows the performance with bid-ask transaction costs and a 0.5% broker fee.

Appendix B

Table B1

Performance of Long-Short TSMOM and RP Strategies without Costs

	1m	2m	3m	6m	9m	12m	RP
Average excess return	-1.1%	5.7%	8.4%	7.0%	7.8%	6.3%	9.6%
Volatility	13.4%	14.1%	14.2%	14.7%	14.7%	15.2%	17.8%
Sharpe Ratio	-0.08	0.40	0.59	0.48	0.53	0.41	0.54
Annualized Alpha	-0.7%	6.1%	8.9%	7.3%	8.0%	6.5%	5.2%
t-Statistic	-0.19	1.63	2.35	1.83	2.02	1.60	2.11
Max Drawdown	58.0%	19.7%	22.4%	30.5%	20.5%	29.7%	43.0%

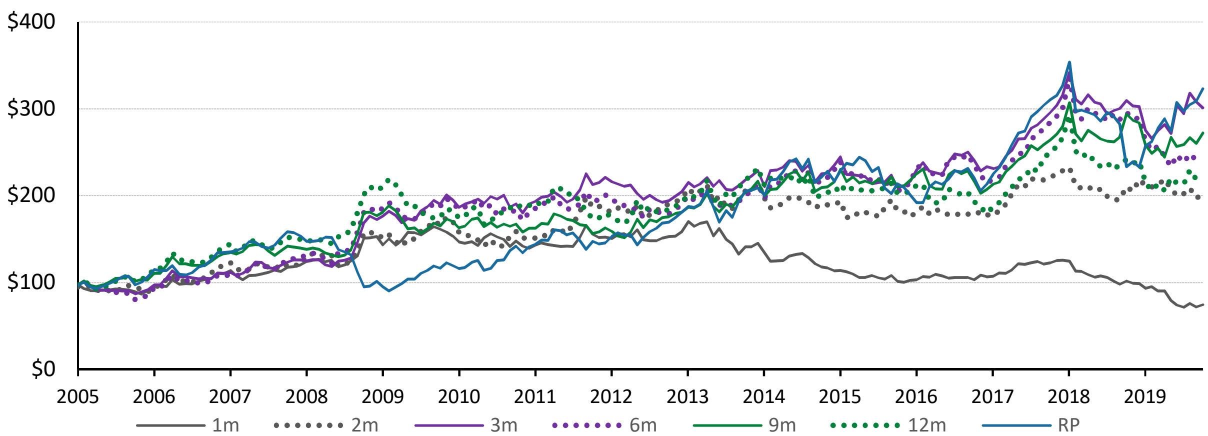


Figure B1. Cumulative returns of Long-Short TSMOM and RP Strategies without Costs from January 2005 to October 2019