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Master of Science in Finance

Master Thesis

Time Series Momentum: Is Trend Following Strategies Viable During Periods With Quantitative Easing?

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Thesis Supervisor:

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Abstract

In regard to the economy following the financial crisis of 2008, we examine time series momentum within 53 financial instruments divided into four asset classes. Our thesis provides evidence of acute repercussions for time series momentum within all assets as a response to the increased correlation, both across- and within-asset classes, deriving from the implementation of quantitative easing. With coordinated movement in the market, fewer individual trends emerge leading to loss of diversification benefits, inferior price predictability and poor performance. As a result time series momentum strategies underperforms in comparison to the market and is, accordingly, unable to generate a significant alpha given the current market conditions.

Contents

List of Figures

List of Tables

1 Introduction

1.1 Background

The efficient market hypothesis suggests current prices should be exhaustively reflected through all information such as past prices and trading volumes. Implicitly, this would mean there is no consistent way of generating profit (loss) from large deviations in the expected/estimated risk-adjusted return, also known as generating abnormal returns. However, empirical evidence finds that simple trend following strategies can systematically generate returns higher than that of the market, challenging the efficient market hypothesis. This is known as generating alpha, which is the excess return systematically generated above a comparable benchmark, and accordingly, measures the performance of a given strategy. If the efficient market hypothesis transpires to be the true source for current prices, the only way to increase an investor's return would be to increase the risk of the underlying investment. These conflicting results between empirical evidence and theoretical hypothesis has caused a divide in the postulation of the true data generating process of current prices, suggesting the possibility of alpha generation by following strategies conducted through technical analysis. Consequently, examination of relevant empirical literature can lead to credible prospects of trend strategies systematically beating the market. One significant example of such empirical literature is the findings in the paper "Time series momentum" published by Moskowitz et al. (2012). Their findings have initiated new research on trend following strategies which has given rise to further advancement on the subject matter as well as presented appealing opportunities for inclined investors.

Strategies for achieving alpha have been sought after for a long time and is evidently also very applicable in today's market. By exploiting different tools such as risk management, drawdown control, and portfolio diversification, one could examine and identify potential ways to improve trading strategies, and in turn consistently generate alpha. Moreover, by active portfolio management and alteration of viable diversification choices, one could opt to either hedge, by investing in different financial instrument with different time horizon to reduce the undertaken risk of the portfolio, or to shift the exposure to attain assets in which possible trends like time-series momentum is present.

One conspicuous query proving decisive in advocating abnormal return generation is how there can be such a peculiar discrepancy on the simple topic of the data generating process of current prices. According to Burton G. Malkiel:

> The efficient market hypothesis is associated with the idea of a "random walk," […]. The logic of the random walk idea is that if the flow of information is unimpeded and information is immediately reflected in stock prices, then tomorrow's price change will reflect only tomorrow's news and will be independent of the price changes today. But news is by definition unpredictable, and, thus, resulting price changes must be unpredictable and random. As a result, prices fully reflect all known information […]. (Malkiel, 2003, p. 59)

The prominence of prices fully reflecting all information evidently relies heavily on symmetric information and the assumption and idea that the flow of information is persistently unimpeded. Furthermore, Burton G. Malkiel concludes that:

> As long as stock markets exist, the collective judgment of investors will sometimes make mistakes. Undoubtedly, some market participants are demonstrably less than rational. As a result, pricing irregularities and even predictable patterns in stock returns can appear over time and even persist for short periods. […]. Undoubtedly, with the passage of time and with the increasing sophistication of our databases and empirical techniques, we will document further apparent departures from efficiency and further patterns in the development of stock returns. (Malkiel, 2003, p. 80)

Clearly, measuring the flow of information proves to be a difficult task. In consolidation with various irrational market participants and pricing irregularities, the occurrence of uncertainty and disagreement is not unexpected. Afterall, this dispute hinges on both subjective perception and empirical evidence. Inevitably, these different opinions on an otherwise unclear verity serves as an intrinsic motivation to several economic agents exploring for profitable strategies and investments.

Over the years, beating the market has always been a coveted achievement amongst investors and is just as relevant today. Consequently, as technology advance and research progress, both modern methods and solutions as well as improved databases emerge, paving the road for new elaborate strategies to systematically attempt to generate alpha. Conversely, the engagement of strategies in financial markets entails a greater risk exposure, predisposing investors to the effects and consequences induced by the pertinent macro trends. In particular, the financial crisis of 2008 immensely affected the market, encouraging the implementation of several governmental countermeasures, one of which called *quantitative easing* (QE). Moreover, in 2012 Tobias J. Moskowitz, Yao Hua Ooi and Lasse Heje Pedersen published an article regarding the effect of "time series momentum", which has inspired several studies referencing this phenomenon consolidated with other trends and strategies. Similarly, their analysis combined with the implementation of QE lay the fundamental premise for our thesis.

1.2 Research Question and Thesis Objective

As technology, research, and other supporting constituents keep synergically developing, intriguing possibilities continuously arise as time passes. Accordingly, new pervasive predicaments and issues contemporaneously emerge with time, contesting the prevalent postulations. This continuous development combined with the preliminary dispute between the efficient market hypothesis and other empirical evidence, specifically time series momentum (Moskowitz et al., 2012), makes for both compelling- and degrading- prospects, concertedly constituting our research question and thesis objective. By trailing the analysis of Moskowitz et al. (2012) and incorporating our own technical analysis, we seek to answer the research question:

> *"Is time series momentum a viable strategy in periods affected by quantitative easing?"*

Answering this question instigates the objective of our thesis which is to identify both the presence of time series momentum and the feasibility of a time series momentum strategy following the financial crisis of 2008 and its reverberations.

1.3 Motivation and Contribution

In the article "Time series momentum", Moskowitz et al. (2012) study the effects of time series momentum within a timeframe starting in 1985 and ambivalently ending in 2009. Coincidentally, at the end of this period many financial instruments experienced a rapid crash as a response to the downturn inflicted by the financial crisis of 2008. Conventionally, time series momentum is proven to be robust throughout the largest crisis throughout history (Hurst et al., 2014). However, the strategy performs sub-optimal during sharp drawdowns, simply because it responds to slowly (i.e., taking a position). Nevertheless, Hurst et al. (2014) find evidence supporting over a century of time series momentum robustness, with adequate performance in periods predisposed to various macro trends. In general, they find higher returns and lower volatility in comparison to the overall market, defined as a 60/40 stock/bond portfolio. However, their research also suggests time series momentum perform worse under periods with high correlation across markets and asset classes.

In our thesis we look at how the intervention from the US Central Bank effectively alters the advantageous attributes of time series momentum. After the global financial crisis of 2008 the Federal Reserve decided to implement a new tool in their monetary policy, namely quantitative easing. We signify this transition by distinguish between the period before and after the inauguration of QE, as pre- and post- QE respectively. Since the implementation, QE has effectively increased the Federal Reserve balance sheet by tenfold, while the post QE market conditions is characterized by high liquidity, elevated prices, and low interest rates, in addition to increased correlations. Broadly recounted, with the post QE period taken into consideration, we observe the progressive increments in correlation between futures contracts and examine how this affects the qualities and characteristic features of time series momentum strategies.

Although some earlier papers have researched the effects of QE on time series momentum (i.e., Georgopoulou & Wang, 2016), no single study has investigated the latest ramifications, which includes arguably one of the most conspicuous and the overall steepest increase in the FED's balance sheet post QE as well as historically low short-term interest rates. Our thesis provides new insights to the subject and contributes to the literature by incorporating a more recent and comprehensive review over a prolonged sample period. Consecutively, our sample consolidates the most recent round of QE as well as giving more insight on the "long-term" implications of the earlies rounds of QE.

2 Literature Review and Theory

2.1 Time Series Momentum

The term *time series* momentum is fundamentally related to *normal* momentum, but different in the sense that rather than focusing on the relative returns in the cross-section (performance compared to peers), time series momentum focuses purely on a security's own past return. Moskowitz et al. (2012) examine 58 different liquid instruments, in which they document significant and consistent time series momentum for assets within the asset classes equity index, currency, commodity, and bond futures. They find strong consistent positive predictability in time series momentum across very different asset classes and markets over 25 years of data. Additionally, the past 12-month excess return of each instrument proves to be a positive predictor of its future return, all the while the 12-month time series momentum profits are positive, not just on average across these assets, but for each liquid instrument they examine (58 in total). They document a robust manifestation across numerous subsamples, look-back periods, and holding periods with the effect persisting for approximately one year before partially reversing over longer horizons.

Based on the methodology presented in the article Time series momentum by Moskowitz et al. (2012), we will expand on the topic of time series momentum and its revolving parts. The initial premise of our main analysis consists of composing a similar strategy on a post QE sample, in addition to repeating the process for data over the timeframe 1965-2021 to be used as a comparative sample including both the pre- and post- QE period. Seeing as we are comparing various asset classes with immensely different and inconsistent standard deviations (Appendix A), we normalize the returns to make them more compatible. In general, we scale the returns for each instrument by their ex-ante volatility before aggregating our time series momentum portfolio. Sequentially, to assess the proficiency in the price predictability of the strategy, we run a pooled panel regression with the scaled return as the dependent variable, while the covariates are set as the dependent variable's own lags, ranging from one to 60. The resulting clustered *t*-statistics stipulates the significance of any apparent trend in price continuation and reversal, providing evidence towards the predictive ability of the strategy. In succession, we determine the profitability of the strategy by regressing the return on different market factors, enabling a perception of to what extent these factors are responsible for the return achieved by the strategy. Conformably, the return achieved which is not explained by the factors is effectively the endowments of the strategy, otherwise known as alpha. We evaluate the strategy against the MSCI World Equity Index, the Barclays Aggregate Bond Index, the S&P GSCI Index, the Fama French stock market factors SMB, HML, and UMD, as well as the value- and momentum- "everywhere" factors from Asness et al. (2013). Additionally, we explore the relationship and differences between time series momentum and cross-sectional momentum and identify how cross-sectional momentum contributes to- and is affected by- the variation in time series momentum returns. Ultimately, we compile our findings to an articulate conclusion by appraising the gradual change in correlation within our instruments with regards to the elaborate effects of QE.

2.2 A Century of Evidence on Trend-following Investing

In the article "A century of evidence on trend-following investing", Hurst et al. (2017) carry out an extensive study on time series momentum across global markets starting in 1880. With clear limitations on accessibility of futures data, they construct a time series momentum strategy using historical data from a range of different sources. They find that time series momentum exhibits exemplary performance during eight out of ten the largest crises throughout the century, which is defined by identifying the largest drawdowns for a 60/40 stock/bond portfolio. In addition, their results argue the same to be true during periods characterized by different macro environments such as economic recessions and booms, war and peacetime, high and low-interest rates, and high and low inflation periods. Conversely, they provide evidence on what seems to be the key detrimental driver in the performance of time series momentum, namely the correlation across- and within- asset classes, suggesting time series momentum strategies perform best during low correlation periods, and worst during high correlation periods.

2.3 Quantitative Easing

Quantitative easing (QE) is a “new” unconventional monetary policy implemented by The United States Central Bank, also known as the Federal Reserve (FED). The endmost purpose of the initiation of QE is to promote economic activity and support economic growth. In general, this implies increasing the total assets in their balance sheet to eventually decrease long-term interest rates (Kiley, 2018), which is achieved predominantly by acquiring long-term securities. More specifically, as the FED continuously bids up securities, the interest rates on them subsequently decrease. While doing so, the FED introduce more money into the economy, increasing the total money supply and thus artificially increase inflation. Signaling theory might suggest that by executing such monetary policies, the government emits a signal to continuously maintain provisions in order to accommodate the intended outcome, all the while reduced interest rates establish more favorable terms for borrowing. In turn, economic agents interpret these prospects and inherently expect less overall risk and prosperous market conditions, inclining them to invest at the present time, which successively has a positive effect on the stock market. However, several economists have expressed their uncertainty on the comprehensive effectiveness of unconventional monetary policies, questioning the FED’s ability to have a positive long-term impact. Moreover, we specify that we do not study the economic effects of QE in its entirety, but rather the implicit effect on time series momentum.

The primary responsibility of the FED is to promote the health of the U.S. economy and the overall stability in the U.S. financial system (Board of Governors of the Financial System, 2022a). To maintain stability in the American economy, the FED has several tools at their disposal in which they can implement as monetary policies. Two of the main tools are either regulating interest rates (Discount Window and Discount Rate) or QE (Open Market Operations) (Board of Governors of the Financial System, 2022b). While they have regulated interest rates for a long time, QE has only been implemented four times in total, with the first occurrence originating as a response to the financial crises of 2008. In the following years QE transpired in three more rounds, specifically in 2010, 2012, and 2020, where the latest, and also the largest, was implemented as a response to the covid-19 pandemic. In conjunction with monetary strategies, the Federal Reserve’s balance sheet gets increasingly complicated and has since late 2008 increased from 900 billion dollars to 8.9 trillion dollars by April 2022 (Board of Governors of the Financial System, 2022c). The assets in the balance sheet consist of U.S. treasury securities, federal agency debt, mortgage-backed securities, conventional lending to financial entities, Section 13(3) emergency lending facilities, among others. The biggest assets include U.S. treasury securities, federal agency debt and mortgage-backed securities.

Parenthetically, the enforcement of such monetary policies and strategies is neither universally “new” nor exclusive to the US per se. The bank of Japan implemented QE in early 2000, while the bank of England and the Central bank of Europe also implemented a similar strategy after the financial crisis of 2008 (Kiley, 2018). Nevertheless, we solely focus on the quantitative easing by the Federal Reserve in the US. As a terminating policy, the Federal Reserve implemented a strategy of *quantitative tightening* in 2022 (Board of Governors of the Financial System, 2022d). This broadly means they cease purchasing securities and rather commence unwinding QE positions. In other words, they reduce their balance sheet by either selling securities in the open market or simply leaving the securities until they expire, in which the supply is “cut out”.

Overall, monetary policies are intended to induce economic stimulation, whereby prompting expectation of beneficial market conditions, and eventually push up asset prices. The increscent change across assets naturally translates to co-movement in said assets, implying heightened correlation across the market. Hence, the underlying conjectures of diminishing diversification benefits stems from the imputation of QE precipitating fewer independent market trends. However, the apparent change in correlation is most certainly an elaborate product of several factors, not merely due to QE and the ensuing market expectations. Additionally, as we exclusively examine the initiative of the FED, i.e., only in the U.S., there are obvious limitations in our models and estimations. By following the methodology as presented in Section 3, we examine how the FED’s implementation of monetary policies, specifically QE, affects time series momentum. Furthermore, by comparing our results with Moskowitz et al. (2012), we elucidate the difference between pre- and post- QE prospects of time series momentum and ultimately distinguish a detrimental relation between time series momentum and QE.

2.4 Hypotheses

Time series momentum strategies are characterized by delivering the best results during extreme market conditions, in addition to taking advantage of trends in different assets, providing a fundamental diversification effect to the strategy. In the aftermath of both the financial crisis in 2008 and the implementation of QE, the equity market has delivered substantial results, realizing positive returns in 12 out of 13 years. With quantitative easing, low-interest rates, and low inflation, investors are encouraged to invest across the pool of available assets rather than exclusively in capital markets, while being more inclined to assume more risk in order to realize a positive excess return. Intuitively, a time series momentum strategy would seemingly prosper during this period. However, during the early post QE period the correlation between futures rose to a new high, implying a diminishing diversification benefit within the strategy as fewer unique trends was presented by the market, ultimately suggesting an impairment in the fundamentals of the strategy.

As this is a relatively "new" monetary policy, there has not been conducted sufficient research on the topic to explicitly document the full extent of its effects. However, as the comprehensive market response remains indecisive, contemporary evidence suggests an interim positive effect on the overall economy and correspondingly on the stock market (Rogers et al., 2014). This intuitively makes sense, as the main purpose of QE is implemented to support economic growth. Subsequently, an overall positive increase in the economic activity may further imply an increase in the correlation across assets, hence indicating possible ripple effects with indirect negative repercussions towards predisposed economic agents.

This leads to our hypothesis which suggests, in the presence of the contemporary market conditions imposed by QE, time series momentum is under pressure as a trend-following strategy and consequently incapable of delivering a significant alpha. Accordingly, we test the viability- and examine the quality- of time series momentum strategies and its distinct attributes.

3 Methodology

Our analysis is broadly carried out in a manner centered around the structure and decomposition of Time series momentum (Moskowitz et al., 2012). Primarily, all relevant data is rudimentary organized in Microsoft Excel prior to being transferred to RStudio where we carry out the pre-eminent methodology, calculations, and endorsement of our data. The following parts of this chapter chronologically describes in detail the structuring and procedures used to derive our prerequisite results leading to our main analysis. All relevant figures and tables are presented in Section 5.

3.1 Ex-ante Volatility Estimate

To allow for comparison between instruments with extensive cross-sectional fluctuation in volatility, we standardize every single instrument by scaling their return by their volatility, whereby making them compatible. More specifically, we derive the ex-ante volatility σ_t for each instrument at each observed datapoint t from the ex-ante annualized variance σ_t^2, by employing an exponentially weighted lagged squared daily returns model:

$$\sigma_t^2 = 252 \sum_{i=0}^{\infty} (1-\lambda)\lambda^i (r_{t-1-i} - \bar{r}_t)^2 \qquad (1)$$

The model incorporates a scalar of 252 to annualize the variance, while the term $(1-\lambda)\lambda^i$ sums up to one such that there is a weighted average across the lagged observations at time t. Calibration of the persistence parameter λ determines the $t-i$ amount of weight assigned, in which the model essentially assigns greater weight to more recent observations and subsequently decrease the weight assigned to more distant observations, as $\lim_{i\to\infty}(1-\lambda)\lambda^i = 0$. The parameter λ is chosen such that the center of mass (CoM) of the weights is 60 days.

3.1.1 Center of Mass

To achieve a CoM of 60 days (Section 3.1), we initialize a model where we set weight at lag i to: $W_i = (1-\lambda)\lambda^i$, distance/position at lag i to: $D_i = i - 1$ and weighted distance at lag i to: $X_i = W_i * D_i$. Correspondingly, the CoM is calculated as:

$$CoM = \frac{\sum_{i=0}^{\infty} X_i}{\sum_{i=0}^{\infty} W_i} = \frac{\sum_{i=0}^{\infty} W_i D_i}{\sum_{i=0}^{\infty} 100\%} = \sum_{i=0}^{\infty} (1-\lambda)\lambda^i (i-1)$$

To get the correct value of λ, we set λ to an arbitrarily high number and commence by trial and error. The CoM is positioned at 60 days by adjusting λ, accurately dispersing the weights across lags ($\lambda = 0.9836066$). By the decaying nature of exponentially lagged weighted averages, the weights become approximately equal to zero after a certain number of lags, roughly 950 in our case, allowing us to neglect lags after this specific point. Moreover, we set a limit of minimum number of lags required to include to 450, yielding a CoM of 59.7 days, as any less than this will impose a change in the center of mass closer to 59 days.

3.1.2 Exponentially Weighted Average Return

Similar to ex-ante annualized variance, the exponentially weighted average return $\bar{r}_t$ for each instrument at each point in time is computed as a weighted average with decaying weights for lags of $i \to \infty$:

$$\bar{r}_t = \lambda \bar{r}_{t-1} + (1-\lambda) * r_t = \sum_{i=0}^{\infty} (1-\lambda)\lambda^i r_{t-i}$$

3.2 Time Series Momentum Predictability

To study time series momentum predictability of futures returns across various time horizons, we run a pooled panel regression. We regress the excess return for every financial instrument in any given month on its return lagged $h = 1, \dots, 60$ months, where the returns in all months are scaled by their ex-ante volatility:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h \frac{r_{t-h}^s}{\sigma_{t-h-1}^s} + \varepsilon_t^s \quad (2)$$

By congregating our instruments across time, the resulting *t*-statistic delineate time-categorized clustering classified by months. Conjointly, we run an auxiliary analogous regression, differentiating by only gauging the sign of past returns:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h sign(r_{t-h}^s) + \varepsilon_t^s \tag{3}$$

3.3 Composite Establishment of Time Series Momentum Portfolio

Following up on our regression results, we assess the alleged existence and continuation of time series momentum by examining trading strategies spanning various time periods. We construct portfolios based on pre-defined signals, in which we reconcile past returns over different "look-back periods" of lags ranging from $k = 1, 3, 6, 9, 12, 24, 36, 48$ months to determine which position to enter. The signal is specified as "sign" (either +1 or -1), contingent on whether the past k month return is positive or negative. +1 denotes entering a long position and -1 denotes entering a short position, where, for all different look-back periods, the assumed position each month is set to the inverse ex-ante volatility: $1/\sigma_{t-1}^s$. Mathematically, the signal and position (P_t^s) can be expressed as:

$$Signal_{k,t}^s = sign\left(r_{t-k,t}^s\right) = sign\left(\frac{Cumret_t}{Cumret_{t-k}} - 1\right)$$

$$P_t^s = \frac{1}{\sigma_{t-1}^s}$$

We then construct a portfolio for each instrument s and look-back period k consistent with the respective signal and position each month. For each portfolio, one could implement "holding periods" of $h = 1, 3, 6, 9, 12, 24, 36, 48$ months, introducing several possible strategies for potentially achieving a positive alpha. However, for simplicity, we solely focus on a holding period of one month, this being the most significant holding period (Moskowitz et al., 2012) as well as the leading presupposition when advancing with our analysis. By implementing trading strategy (k, h), we derive a single equal weighted "diversified" time series momentum portfolio either by averaging the return across all instruments or "asset class specific" by separately aggregating the instruments with respect to each asset class. The resulting return for instrument s at time t, given strategy (k,h) is calculated as:

$$r_{t,t+h}^{TSM(k,h),s} = Signal_{k,t}^{s} P_t^s r_{t,t+h}^{s} \tag{4}$$

3.4 Time Series Momentum Performance

To evaluate the impending performance of the various strategies as well as their abnormal capability to generate alpha, we individually regress each portfolio return (diversified and assets class specific), $r_{t,t+1}^{TSM(k,1)}$, on the MSCI World Index (MSCI), the Bloomberg US Aggregate Bond Index (BOND), and the S&P GSCI Index (GSCI), in addition to the Fama-French factors SMB, HML and UMD, adjusting for passive market premiums and exposure:

$$\begin{aligned} r_t^{TSM(k,1),s} = \alpha + \beta_1 MSCI_t + \beta_2 BOND_t + \beta_3 GSCI_t + \beta_4 SMB_t + \beta_5 HML_t \\ + \beta_6 UMD_t + \varepsilon_t \end{aligned} \tag{5}$$

3.5 Explicit Time Series Momentum Portfolio

Moving forward in our thesis, we form an explicit time series momentum portfolio denoted as "TSMOM", which serves as the predominant representation of time series momentum. By following our trading strategy approach delineated in Section 3.3, the portfolio is formed by considering a 12 month look-back period and a 1 month holding period. For comparison across assets and portfolios, we follow Moskowitz et al. (2012) and size each position to be $40\%/\sigma_{t-1}^{s}$, resulting in an average equal-weighted return of the diversified portfolio across assets at time t to be:

$$r_{t,t+1}^{TSMOM} = \frac{1}{S_t} \sum_{s=1}^{S_t} sign\left(r_{t-12,t}^{s}\right) \frac{40\%}{\sigma_t^s} r_{t,t+1}^{s} \tag{6}$$

3.5.1 Passive Long Portfolio

In addition to our explicit TSMOM portfolio we form an otherwise identical portfolio on the basis of always being long the asset, which is mainly used as a comparative strategy:

$$r_{t,t+1}^{TSMOM(long)} = \frac{1}{S_t}\sum_{s=1}^{S_t}\frac{40\%}{\sigma_t^s}r_{t,t+1}^s \qquad (7)$$

3.6 Risk Adjusted Alpha

As a measure of performance we employ the term “alpha”, which is used to describe the capability of TSMOM to generate a return higher than that of the market and is measured through the intercept of the respective regression.

To assess the alpha generating capabilities and factor dependency of the diversified TSMOM portfolio, we regress the return of the strategy on the MSCI World Index, (MSCI), and the Fama-French factors SMB, HML and UMD (Equation 8). In addition, we run an analogous regression replacing the Fama-French factors with the across-asset-classes factors (Asness et al., 2013) value- (VAL) and momentum- (MOM) “everywhere” (Equation 9).

$$r_t^{TSMOM} = \alpha + \beta_1 MSCI_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t \qquad (8)$$

$$r_t^{TSMOM} = \alpha + \beta_1 MSCI_t + \beta_2 VAL_t + \beta_3 MOM_t + \varepsilon_t \qquad (9)$$

3.7 Correlation

The correlation structure of both TSMOM and the passive long portfolio may be divided into two main categories, namely average pairwise correlation within each asset class and average correlation across asset classes. Average pairwise correlation within each asset class is calculated by computing the monthly correlation between all combinations of the instruments within each asset class and subsequently averaging them (excluding each instruments correlation with itself). The average correlation across asset classes is simply the monthly correlation between the asset class specific TSMOM portfolios (constructed with respect to only one asset class).

3.7.1 Rolling Correlation

In addition to standard sample correlation, we compute the TSMOM 36-month rolling average absolute correlation, both pairwise within each asset class and across asset classes. Both categories are calculated in a similar fashion as in Section 3.7, differentiating by using only the absolute values over the past 36 months, resulting in a fluctuating correlation across time. This is convenient as it not only eliminates potential longevous spurious correlations, but sequentially it accommodates comparison between historical sample correlation and contemporaneous correlation, identifying coeval directional trends in correlation. However, decreasing the calculation sample may introduce estimation flaws as a result of inadequate data, potentially imposing errors in our correlation calculation. Nevertheless, the rolling correlations will predominantly be used as an approximation to determine the directional trend, mitigating this superficial issue.

3.8 Cross-sectional Momentum

Cross-sectional momentum is broadly defined as an asset's performance in relative to peers. In accordance with Asness et al. (2013) we derive a cross-sectional momentum strategy consisting of all our instruments, contingent on their relative cross-sectional performance. Similar to TSMOM (Section 3.3), we define a signal on whether to go long or short the asset at time t based on the assets past 12-month cumulative return, skipping the previous month's return to circumvent possible reversals in the price of the instruments:

$$Signal_t^s = r_{t-12,t-1}^s = \frac{Cumret_{t-1}}{Cumret_{t-12}} - 1$$

For each t, we cross-sectionally compare each assets signal and subsequently rank their cumulative return in ascending order. In turn, based on their relative rank, we obtain the weight of each asset, w_t^s, and position taken, p_t^s, which are defined as:

$$w_t^s = \frac{Rank_t^s - Rank_t^{median}}{S_t}, \qquad Rank_t = 1, \dots, S_t$$

$$p_t^s \propto \left| \frac{Rank_t^s - Rank_t^{median}}{Rank_t^{median}} \right|$$

By following this strategy, we obtain our diversified cross-sectional portfolio, denoted XSMOM, where the weighted average return at any time t is:

$$r_{t,t+1}^{XSMOM} = \sum_{s=1}^{S_t} w_t^s \, p_t^s r_{t,t+1}^s \qquad (10)$$

3.8.1 Time Series Momentum v. Cross-sectional Momentum

According to Moskowitz et al. (2012), time series momentum and cross-sectional momentum have a distinctly concomitant connection. To determine if time series momentum manifests a significant alpha beyond the explanatory power of cross-sectional momentum post QE, we investigate the inherent connection by regressing both the diversified- (ALL) and asset class specific- (COM, EQ, FI, FX) TSMOM portfolio i on both the diversified- and asset class specific XSMOM portfolio j:

$$r_t^{TSMOM_i} = \alpha + \sum_{j=1}^{J} \beta_j r_t^{XSMOM_j} + \varepsilon_t \qquad (11)$$

3.9 The Effect of TSMOM on Other Factors

From the following sub-section we compliment Section 3.8.1 and appraise the account of the explanatory power of TSMOM on cross sectional momentum and the Fama-French factors UMD, HML and SMB. We separately regress both the diversified- and asset class specific XSMOM portfolio, as well as each Fama-French, on the diversified TSMOM portfolio:

$$factor_i = \alpha + \beta_1 r_t^{TSMOM} + \varepsilon_t \qquad (12)$$

3.10 Quantitative Easing v. TSMOM

Since late 2008, the economy has been significantly influenced by the institution of QE. This begs the question of to what extent QE has contaminated the effects of time series momentum over the last decade. By looking at the FED balance sheet, we develop a new variable to incorporate the change in the balance sheet over the post QE period (Equation 13). Keeping consequential, we regress the diversified

TSMOM portfolio on the same covariates as in Equations 5, 8, and 9, with the inclusion of the QE factor (Equations 15, 16, and 17), in addition to regressing both our diversified- and asset class specific TSMOM portfolio i on QE (Equation 14).

$$\Delta QE_t = \frac{QE_t}{QE_{t-1}} - 1 \tag{13}$$

$$r_t^{TSMOM_i} = \alpha + \beta_1 \Delta QE_t + \varepsilon_t \tag{14}$$

$$r_t^{TSMOM} = \alpha + \beta_1 MSCI_t + \beta_2 BOND_t + \beta_3 GSCI_t + \beta_4 SMB_t + \beta_5 HML_t + \beta_6 UMD_t + \beta_7 \Delta QE_t + \varepsilon_t \tag{15}$$

$$r_t^{TSMOM} = \alpha + \beta_1 MSCI_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 \Delta QE_t + \varepsilon_t \tag{16}$$

$$r_t^{TSMOM} = \alpha + \beta_1 MSCI_t + \beta_2 VAL_t + \beta_3 MOM_t + \beta_4 \Delta QE_t + \varepsilon_t \tag{17}$$

4 Data

In the following chapter we present both our raw- and secondary- data which is employed in order to compile a sound analysis and ultimately reach our culminating results. Our analysis is predominantly encompassing a quantitative approach by trailing the framework of Moskowitz et al. (2012), applied primarily to monthly data in the following consecutive period leading up to 2022 (post QE). By specifically examining this time period, we investigate the presumed reverberations from quantitative easing on time series momentum. In addition, we have gathered data starting in 1965, which is mainly used as a comparative sample for collective comparison in conjunction with the results of Moskowitz et al. (2012) starting in 1984. Moreover, as TSMOM is conditional on its signal we include 12-months lagged data for the calculation of the portfolio returns, while the main analysis is conglomerated over the period following December 2009 (and 1984), making the first realized return materialize in January the subsequent year.

4.1 Futures and Forwards

To the extent we are conduct research based on the findings and framework of Moskowitz et al. (2012) and to make valid comparisons, we strive to collect the equivalent data as in their article. This entails collecting financial data on futures- and forward contracts from nine country equity indices and 13 government bonds, both from developed countries, 24 commodities, and nine initial currencies being transfigured to 12 cross-currency pairs, adding up to 58 instruments in total. These instruments are chosen as they are amongst the most liquid in the world (Moskowitz et al. 2012, p230), inducing mitigation against returns being tainted by illiquidity and stale prices. Additionally, the high liquidity reduces slippage in the market, coherently enabling a more pragmatic realization of a strategy by any financial institution. Through the databases Bloomberg and Refinitiv Eikon we managed to procure daily data on the first continuation, which is the most liquid and closest to expiration, for most of the instruments (53 in total) in the time period from January 1965 through December 2021. While most of the instruments include sufficiently lengthy data, the starting point varies across the sample, ranging up to 2005. The raw data acts as the starting point of our analysis, whereby we calculate both the daily- and monthly- excess return for each futures contract in which we need to carry on with our methodology. As futures prices are conveniently set on the basis of spot price and risk-free rate, excess returns on futures contracts are simply calculated as the change in futures prices. We refer to futures' excess returns by the terms "excess return" and "return" interchangeably. Moreover, given the limited breadth and liquidity in instruments, Moskowitz et al. (2012) only reports results after 1985, hence, we do the same for our comparative sample.

4.1.1 Commodities

We use the following 24 Commodities: Aluminum, Brent Crude, Live Cattle, Cocoa, Coffee, Copper, Corn, Cotton, Crude Oil WTI, Gasoil, Gold, Heating Oil, Lean Hogs, Nickel, Platinum, Silver, Soybeans, Soymeal, Soy Oil, Sugar, RBOB Gasoline Spliced with unleaded Gasoline, Wheat, and Zinc.

4.1.2 Bonds

We use the following eleven Bonds: Euro Schatz, Euro Bobl, Euro Bund, Euro Buxl, Canada 10-year Bond, Japan 10-year Bond (TSE), Long Gilt, US 2-year Note, US 5-year Note, US 10-year Note, and US Long Bond.

4.1.3 Equity Indices

We use the following nine developed equity indices: ASX SPI 200 (Australia), DAX (Germany), IBEX 35 (Spain), CAC 40 (France), FTSE/MIB (Italy), TOPIX (Japan), AEX (Netherlands), FTSE 100 (UK), and S&P500 (US)

4.1.4 Currencies

With limitations in access to adequate databases, we make a simplifying adjustment to the currency data, whereas we only use spot exchange rates to calculate excess return (without forward interest rates). We use the following nine currencies: Australian Dollar, Euro, Canadian Dollar, Japanese Yen, Norwegian Krone, New Zealand Dollar, Swedish Krona, Swiss Franc, and Great British Pound.

4.2 Federal Reserve Balance Sheet

To assess the impact of quantitative easing on time series momentum, we extract data from the Balance Sheet of the Federal Reserve (Board of Governors of the Financial System, 2022e). The data ranges from 2008-2022 and specifies the size of the total assets in the balance sheet.

4.3 COT Report – Position of Traders

We also collect data on the position of traders from commodity futures trading commissions (CFTC) by extracting the available data from 1986 on the available instruments (Commodity Futures Trading Commission, 2022). The CFTC requires all large traders to identify as a commercial or non-commercial which Moskowitz et al. (2012), Bessembinder (1992), and De Roon et al. (2000) refers to as hedgers and speculators. We report the open interest, long- and short- position and accordingly identify net speculator position as:

$$Net\ speculator\ position = \frac{Long\ position - Short\ position}{Open\ interest}$$

If the net speculator position is positive, the hedger position will be negative and vice versa. With discrete traders (commercial or non-commercial) there will inevitably be a difference in the reported numbers and actual numbers which is "non-reported", however this is small and insignificant. The summary statistics of net speculator positions are included in Appendix A. While most of the commodities are covered by the report, not all instruments are included as the CFTC only regulates US based indices, bonds, and currencies. We observe a majority of speculators being net-long over the post QE sample, all the while most of the instruments evince a positive annualized mean return, which ostensibly coincides with Moskowitz et al (2012). This can roughly be interpreted as an indication of speculators positioning themselves to take advantage of trends at the expense of hedgers. Moreover, Cotton, Crude, Natural gas, 30-year US, AUD, EUR, JPY, GBP, and S&P500 all have a negative related average net position against the respective annualized mean return.

4.4 Asset Pricing Benchmarks

To evaluate the returns of the various TSM strategies as well as the explicit TSMOM portfolio, we compare their returns to the market proxies specified by the asset pricing benchmarks MSCI World Equity Index, Barclays Aggregate Bond Index, and S&P GSCI Index (Bloomberg, Refinitiv Eikon).

4.5 Risk Factors

To assess the risk-factor exposure of our TSM strategies, we apply the long-short Fama-French factors SMB for size-, HML for value-, and UMD for cross-sectional momentum- premium from Kenneth R. French’s web site (2022), which we simply refer to as the “FF-factors”. Additionally, to account for risk-factor exposure across asset classes, we replace the FF-factors with the long-short value- and cross-sectional momentum- “everywhere” factors from Asness et al. (2013).

5 Results and Analysis

Through our analysis we examine the influential interconnection between external market factors and the immediate effects on time series momentum. By systematically following our methodology, we collate a holistic conclusion from our results which conform to our hypothesis and correspondingly reflects a profound deterioration in the performance of the TSMOM strategy. In addition to our leading analysis, we reconcile our methodology over the period 1985-2009 in accordance with Moskowitz et al. (2012) and attain similar result over the sample, alleviating potential measurement errors and substantiating a valid comparison. Moreover, the level of statistical significance in variables (of which defined in Section 3) is specified in the reported tables by the codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '(*)'.

5.1 Price Continuation, Reversal, and Predictability

Figure 1 exhibits both a striking reduction and a change in the overall sign of the significance of lagged returns' effect on current returns across instruments compared to Moskowitz et al. (2012). We identify a reversal pattern after 26-34 months in commodity, currency, and all instruments aggregated, while bond appears to indicate a positive return continuation for the first six months. Contrarily, equity indicates a negative return continuation the first 16 months and a positive reversal after 39-57 months. However, with only some spread out months transpiring to be significant, the model precipitates no clear pattern in neither return continuation nor reversals for any of the asset classes. Hence, we cannot deduce any credible trend, as none of the alleged patterns evince any coherent statistical significance over the period. This suggests a weak link in determining return continuation and reversals and subsequently price predictability, impairing the inceptive admissibility of time series momentum in the sample period.

Table 1 presents further evidence of the weak price predictability, whereas none of the look-back strategies manages to generate a statistically significant alpha, with the exception of 6-month look-back for bonds which is statistically significant only on a 95% confidence level. Comparably, when running an otherwise identical regression on data within the sample period from 1985 to 2021 (Appendix B), we get a statistically significant alpha on a: 99.9% confidence level on equity (k9, k12, k24), 99% confidence level on equity (k6), bond (k1), and all instruments (k12), 95% confidence level on equity (k3, k48), currency (k1), commodity (k9, k36), and all instruments (k3, k1) and finally 90% confidence level on equity (k36), currency (k6), bond (k3, k48), and all instruments (k6). This substantial divergence in alpha generation capacity may be imposed by an exogenous factor, seemingly prevalent only in the post QE sample. Furthermore, the insignificance of past prices provides evidence of time series momentum being absent in our sample, as there is no presence of "momentum" in the sense that assets' past prices explain current prices.

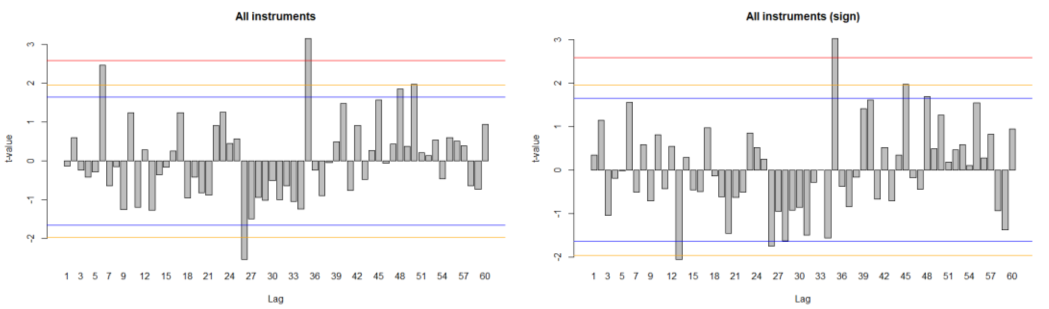
Figure 1

Aggregated pooled t-statistics clustered by time (month) (Equations 2 and 3)

Evaluated against the statistical significance levels: 0.001 (red), 0.01 (orange) and 0.05 (blue)

Sample: December 2009 – December 2021

Panel A: All instruments



Panel B: Asset class specific

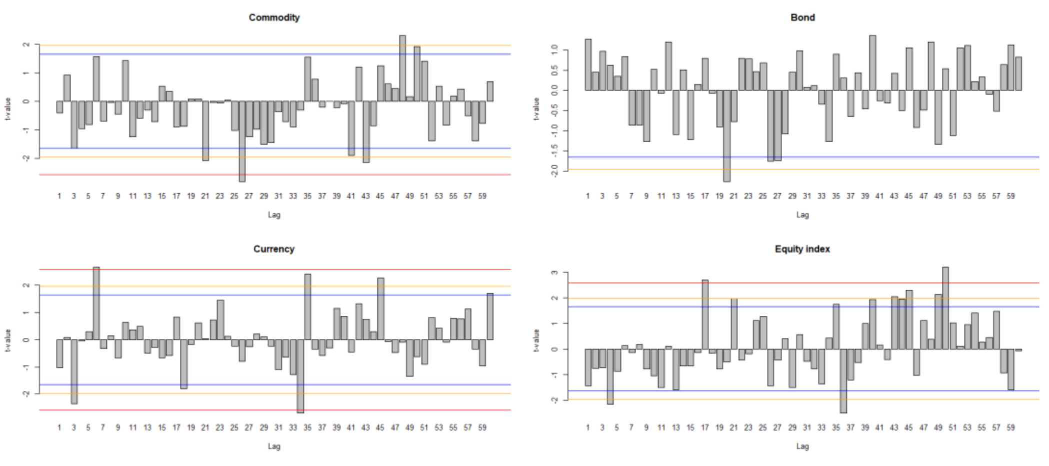


Table 1

t-statistic of alpha (intercept) from regressing time series momentum strategy $(\boldsymbol{k}, \mathbf{1})$ on market proxies and FF-factors in consolidation with various look-back periods (Equation 5)

Sample: December 2009 – December 2021

Look-back period	*1*	*3*	*6*	*9*	*12*	*24*	*36*	*48*
All assets	-0.28	0.09	0.96	0.16	0.44	0.57	-1.43	-0.84
Commodity	0.33	0.11	0.17	-0.41	0.67	0.76	-1.03	-1.28
Equity	-1.07	-0.68	-0.01	0.16	-0.78	0.03	-1.22	0.62
Bond	0.47	1.64	1.93 (*)	1.03	1.33	0.34	-0.42	0.02
Currency	-0.75	-0.98	0.85	-0.07	-0.20	0.30	-0.79	-0.81

5.2 Detrimental Performance

In conjunction with our findings of weak price predictability, TSMOM suffers in the period covering the latest decade. The strategy manages to achieve an annualized Sharpe ratio of 0.11, considerably lower than the annualized Sharpe ratio of 0.57 achieved in the comparable sample period from 1985-2021, while maintaining approximately the same annualized volatility of 15.71% (post QE) and 14.21% (1985-2021). The poor TSMOM performance is neatly illustrated by Figure 2, which explicitly depict a period of stagnation in TSMOM returns emerging in 2009 and lasting throughout the sample period. By inspecting the plot over the post QE period, we can validate the presence of some distinct external factor only impeding TSMOM, whereas the market (MSCI) continuously generates a positive return while the return on TSMOM is at a halt.

Figure 2

Cumulative return of TSMOM and passive long portfolio, as well as an otherwise identical passive long MSCI strategy

Sample: January 1985 – December 2021

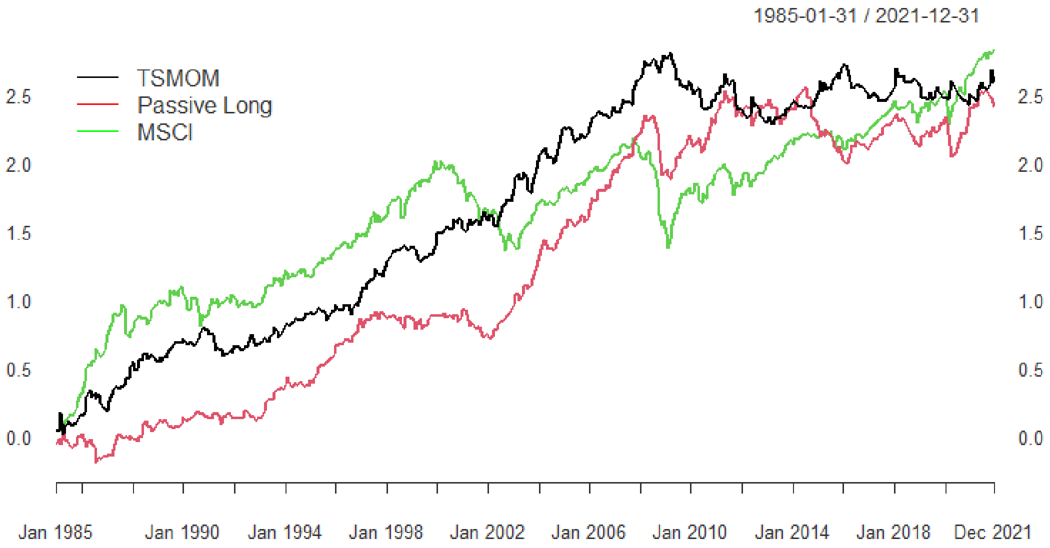


Table 2 exhibits debilitated performance of the TSMOM strategy when regressed on MSCI World and the FF-factors. Our findings indicate the strategy struggles to generate a significant risk adjusted alpha in both the monthly and quarterly cases, while the model overall only explain the TSMOM portfolio return to some degree. Moreover, only UMD of the factor loadings has a significant impact on our TSMOM strategy. We conduct a more comprehensive analysis of this discernible link in Section 5.3. In comparison, the 1985-2021 sample enables the TSMOM strategy to achieve a monthly alpha of 0.63% and a quarterly alpha of 1.49% with respect to MSCI and the FF-factors, where both periodic alphas transpire to be significant with a *t*-statistic of 3.16 and 2.32 respectively (Appendix C). We find similar results by considering the factors value- and momentum- "everywhere", as opposed to the cross-sectional FF-factors. In addition to expressing no sign of exposure to risk-factors across asset classes, TSMOM is unable to achieve significant risk adjusted alpha (Table 3). As with the FF-factors, the TSMOM strategy with respect to MSCI and the "everywhere" factors applied to the 1985-2021 sample precipitates a monthly and quarterly alpha of 0.59% and 1.39%, with a significant *t*-statistic of 2.86 and 2.06 respectively (Appendix D). Evidently, the strategy is incapable of generating a significant alpha in either of the above cases in the post QE sample, supposedly as a response to both the weak price predictability and a loss of diversification benefits. We do not find neither the futile coefficients nor the modest R^2 unexpected however, whereas the market steadily generates positive returns (Figure 2) while TSMOM return stagnates, indicating a lack of causation. Hence, TSMOM does not reap the benefits from any of the respective factor risk premiums nor from a time series momentum factor premium, rationalizing the poor performance.

Table 2

Regression summary: Diversified TSMOM on MSCI World and FF-factors (Equation 8)
Sample: December 2009 – December 2021

		Intercept	*MSCI*	*SMB*	*HML*	*UMD*	R^2
Monthly	*Coefficient* *(t-stat)*	0.14% (0.36)	-0.04 (-0.40)	-0.06 (-0.35)	0.09 (0.57)	0.04 (0.30)	0.5%
Quarterly	*Coefficient* *(t-stat)*	0.14% (0.13)	0.02 (0.13)	0.16 (0.58)	0.11 (0.57)	0.51 * (2.19)	11%

Table 3

Regression summary: Diversified TSMOM on MSCI World and value & momentum "everywhere" factors (Equation 9)
Sample: December 2009 – December 2021

		Intercept	*MSCI*	*VAL*	*MOM*	R^2
Monthly	*Coefficient* *(t-stat)*	0.15% (0.38)	-0.06 (-0.59)	0.10 (0.33)	0.07 (0.24)	0.3%
Quarterly	*Coefficient* *(t-stat)*	0.32% (0.29)	-0.04 (-0.24)	0.08 (0.14)	0.67 (1.36)	6.5%

5.3 Time Series Momentum and Cross-sectional Momentum

The relationship between time series momentum and cross-sectional momentum is presented in Table 6, which describes to what extent XSMOM explains the returns on our TSMOM portfolio. We identify a significant relationship between TSMOM and XSMOM both across the diversified portfolios and independently within each individual asset class, with a cogent R^2 both for the diversified portfolios (52%) and for almost all asset classes, ranging from 63% in commodities (COM) to 4% in bonds (FI). This relation helps explain the significant loading of TSMOM on UMD in Section 5.2. The diversified TSMOM is also significantly related to individual asset-class-compromised XSMOM strategies for commodities, equity indices and currencies. Additionally, TSMOM in commodities is significantly related to

XSMOM in currencies, TSMOM in equity indices is significantly related to XSMOM in commodities and currencies, TSMOM in bonds is significantly related to XSMOM in currencies and TSMOM in currencies is significantly related to XSMOM in equity indices.

However, based on the various intercepts, XSMOM captures most of the premium return on TSMOM in equity indices, bonds, and currencies. Hence, we infer a prevalent relationship across assets, but only establish a significant distinct separation of time series momentum and cross-sectional momentum in the diversified TSMOM and TSMOM in commodity.

Table 4

Regression summary: TSMOM on XSMOM (Equation 11)
Sample: December 2009 – December 2021

	Intercept	*XSMOM ALL*	*XSMOM COM*	*XSMOM EQ*	*XSMOM FI*	*XSMOM FX*	R^2
TSMOM ALL	0.62% * (2.35)	0.14 *** (12.49)					52%
TSMOM ALL	0.60% ** (2.73)		0.09 *** (8.09)	0.13 *** (4.50)	0.05 (0.52)	0.87 *** (9.82)	68%
TSMOM COM	0.79% ** (3.14)		0.19 *** (15.72)				63%
TSMOM COM	0.78% ** (3.30)		0.17 *** (13.53)	-0.02 (-0.65)	-0.03 (-0.34)	0.47 *** (4.86)	69%
TSMOM EQ	0.23% (0.44)			0.68 *** (9.73)			40%
TSMOM EQ	0.54% (1.07)		0.09 ** (3.33)	0.67 *** (10.12)	-0.14 (-0.66)	0.34 (*) (1.68)	48%
TSMOM FI	0.48% (0.89)				0.56 * (2.48)		4%
TSMOM FI	0.63% (1.32)		-0.02 (-0.70)	0.05 (0.77)	0.50 * (2.45)	1.21 *** (6.23)	27%
TSMOM FX	-0.02% (-0.06)					2.16 *** (14.87)	61%
TSMOM FX	0.11% (0.29)		0.03 (1.52)	0.09 (*) (1.74)	-0.09 (-0.55)	2.05 *** (13.05)	62%

We recommence the examination of cross-sectional momentum by reversing the order and regress other factors on TSMOM. Identical to above, we can establish a significant explanation from the diversified TSMOM on both the diversified XSMOM and all asset classes, apart from bonds (Table 5). However, the diversified- and commodity- XSMOM exhibits a significant intercept, indicating an inferior return premium on XSMOM and subsequently a distinction between the two. Moreover, TSMOM does not load significantly on any of the FF-factors, and with an R^2 of 0 for all factors, it is not able to explain any of the variation in these return premiums.

The findings of prevalent relationship both between separate assets classes and diversified across asset classes as well as significant intercept only in diversified- and commodity portfolios, for both TSMOM and XSMOM, conjointly indicate no significant difference in TSMOM and XSMOM for neither equity, bonds nor currency. In fact, the premium achieved by following either one of the momentum strategies in these asset classes appears to be indistinguishable. We do, however, distinguish between the return achieved by TSMOM and XSMOM in commodity and diversified portfolios, where TSMOM actively exceeds XSMOM.

Table 5

Regression summary: XSMOM and FF factors on TSMOM (Equation 12)

Sample: December 2009 – December 2021

	Intercept	*TSMOM ALL*	R^2
XSMOM ALL	-4.00% ** (-2.94)	3.77 *** (12.49)	52%
XSMOM COM	-3.20% * (-2.40)	2.86 *** (9.70)	40%
XSMOM EQ	-0.69% (-1.13)	0.44 ** (3.27)	7%
XSMOM FI	0.08% (0.42)	0.05 (1.22)	1%
XSMOM FX	-0.20% (-1.22)	0.41 *** (11.53)	48%
UMD	0.24% (0.82)	0.03 (0.40)	0%
HML	-0.26% (-1.06)	0.02 (0.30)	0%
SMB	0.06% (0.26)	-0.01 (-0.12)	0%

5.4 Diversification Impairment

A fundamental prerequisite for the success of a time series momentum strategy is proficient utilization of diversification benefits, inclining the strategy to be conditional on the correlation within the confined assets. We consider the progressive change in correlation by cross-examining both the sample average pairwise correlation within asset classes (Table 6) and the sample average correlation across asset classes (Table 7) with the corresponding correlations reported by Moskowitz et al. (2012). In the post QE sample, the average pairwise correlation within asset classes retains its relative structure, i.e. the passive long position within each of the asset classes, apart from currencies, manifest a higher correlation than that of TSMOM. In contrast, all the average pairwise correlations, apart from bonds, increase for both TSMOM and the passive long positions. Furthermore, the TSMOM average correlation across asset classes also retains its relative structure, while, for the passive long positions, the sign of the correlations change, apart from commodities v. equities, and commodities v. currencies. Overall, we observe a general increase in across-asset correlations for TSMOM as well as for the passive long positions, apart from currencies v. bonds.

Table 6

Average pair-wise correlation within asset class (3.7)
Sample: December 2009 – December 2021

	Commodities	*Equities*	*Bonds*	*Currencies*
TSMOM strategies	0.12	0.43	0.19	0.28
Passive long positions	0.23	0.76	0.37	-0.07

Table 7

Average correlation across asset classes (3.7)
Sample: December 2009 – December 2021

	Commodities	*Equities*	*Bonds*	*Currencies*
TSMOM strategies				
Commodities	1			
Equities	0.30	1		
Bonds	0.22	0.21	1	
Currencies	0.52	0.39	0.52	1
Correlations of passive long positions				
Commodities	1			
Equities	0.59	1		
Fixed income	0.14	0.05	1	
Currencies	-0.08	0.18	-0.34	1

We further investigate the relative correlation by comparing the TSMOM 36-month rolling average absolute pair-wise correlation within asset classes with the corresponding historical average absolute correlation (Figure 3). We distinguish a slight increase in the contemporaneous correlation for commodities and bonds, while currency and equity indices reside both above and below the historical average. Moreover, commodities having the lowest correlation among the asset classes, may be responsible for the significant difference between TSMOM and XSMOM within this asset class, justifying the loading of TSMOM on UMD. More notably, Figure 4 illustrates the predominant indication of the time-relative sample correlation across asset classes. Specifically, the TSMOM 36-month rolling average absolute correlation across asset classes has since 2009 continuously persisted above the sample average correlation, revealing a striking increase in across-asset correlation over the corresponding period.

The increscent pairwise- and across-asset- correlation infer a suppression of the antecedent market trend variability, effectively diminishing the diversification benefit. This implies an impairment in the TSMOM strategy, which constitutionally has to conform to the prevailing market conditions. As the premise of the strategy is especially availed by exploitation of trends across different assets, it is accordingly more susceptible to the adverse effects associated with increased correlation. These findings may indicate repercussions of QE on time series momentum, providing both evidence of our preliminary assumptions and further support to our hypothesis.

Figure 3

TSMOM 36-month rolling average absolute pair-wise correlation within asset classes (3.7.1)
Evaluated against the whole-sample historical average absolute correlation within asset classes
Sample: December 1984 – December 2021

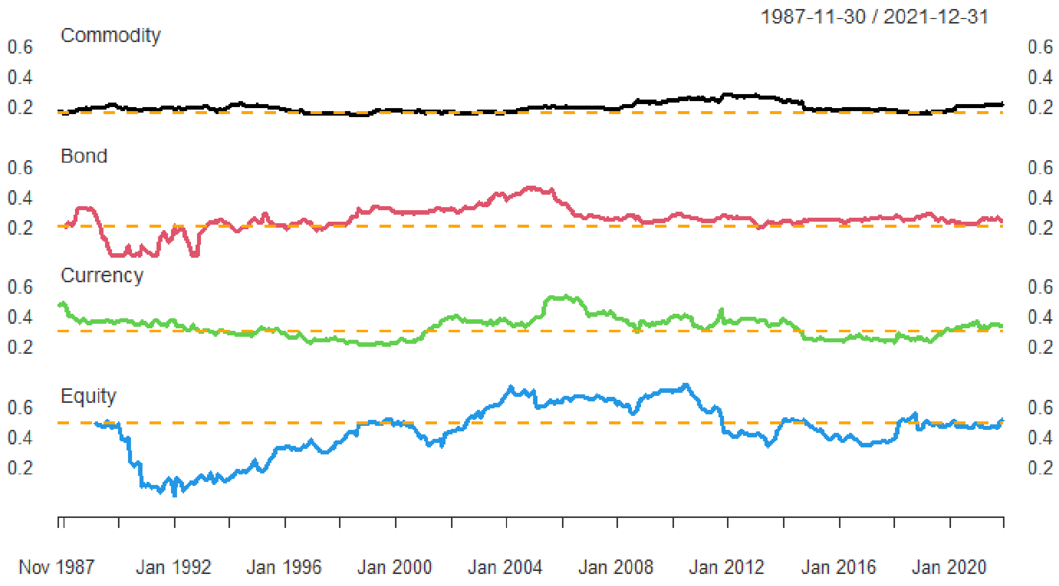
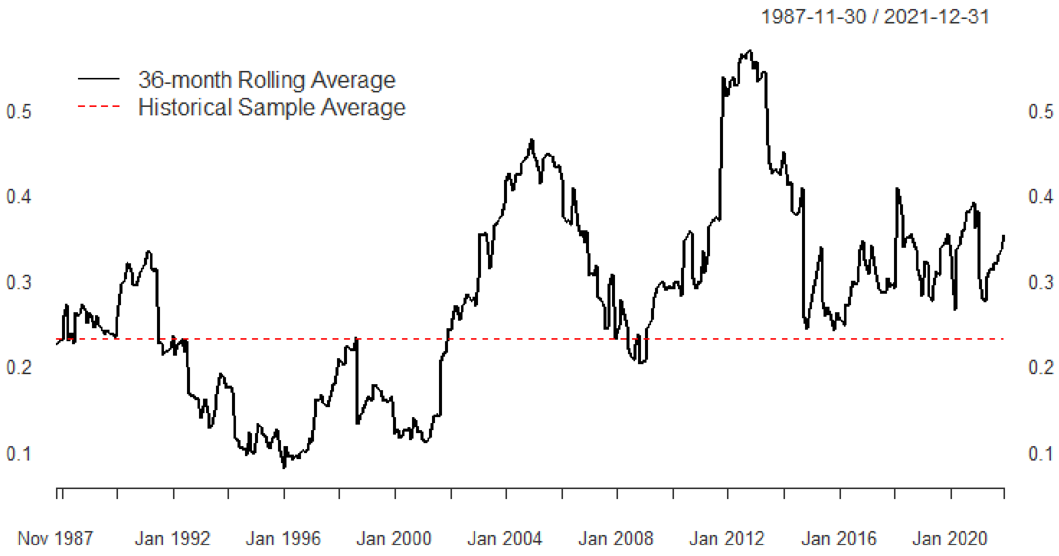


Figure 4

TSMOM 36-month rolling average absolute correlation across asset classes (3.7.1)
Evaluated against the whole-sample historical average absolute correlation across asset classes
Sample: December 1984 – December 2021



5.5 Quantitative Easing and Time Series Momentum

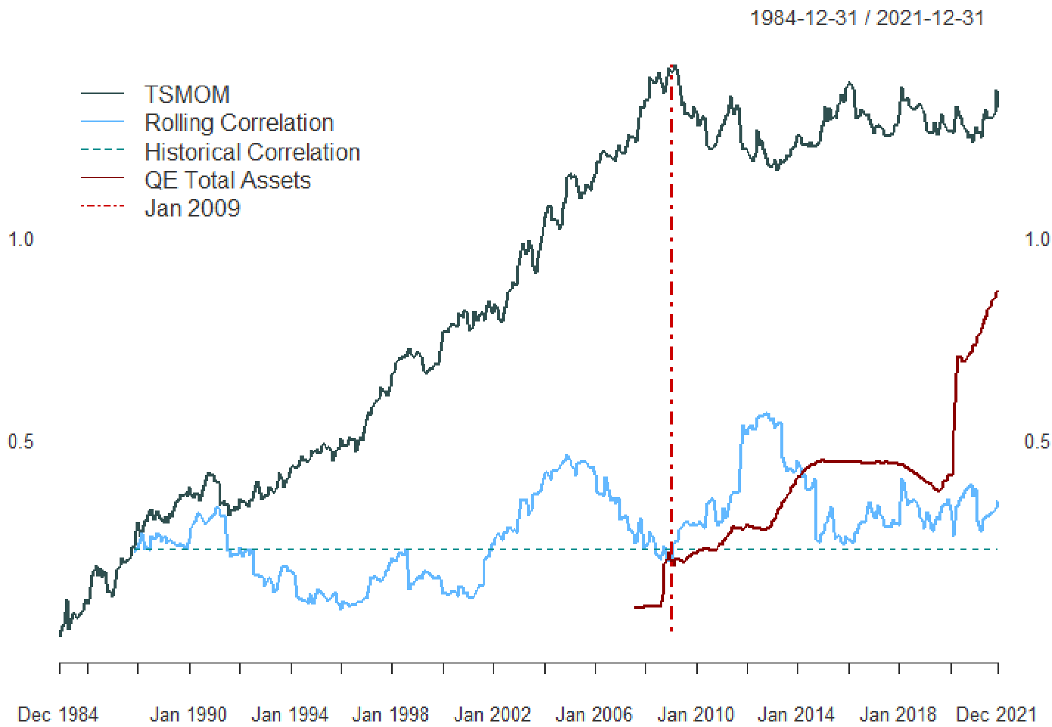
In Section 5.4 we find evidence of an incremental pattern in correlation both across asset and within asset classes. What is interesting about this pattern is the timely occurrence, which coincides with the inception of quantitative easing. Seemingly, the increased correlation has a significant impact on the contemporaneous performance of TSMOM, abruptly imposing a persistent period of stagnation and subsequently prompting the suspicion of QE's repercussion on TSMOM through ripple effects. Figure 5 visually depict a combination of TSMOM return (Figure 3) and the rolling correlation across asset classes (Figure 4), with the addition of total assets in the FED balance sheet (Appendix E), explicitly outlining the pre- and post-QE periods.

Figure 5

Illustration of TSMOM return and 36-month rolling average absolute correlation across asset classes pre- and post- QE

For visual purposes we scale TSMOM returns by 2 and QE total assets by 10,000,000

Sample: December 1984 – December 2021



From the plot, it appears as if QE has a positive effect on correlation and consequentially a negative effect on TSMOM over the period of 2009-2015. We observe a distinct pattern between correlation and TSMOM, as there is a sharp rise in correlation lasting until mid-2013 before declining until the end of 2014, while

TSMOM declines until mid-2013 before increasing until 2016. According to Rogers et al. (2014), unconventional monetary policies like QE becomes less effective when short-term interest rates are approaching zero, which was the case in the period leading up to 2015. This may explain why the correlation decrease when QE increase in 2012 which subsequently leads to the dip followed by positive return in the TSMOM strategy. Over the period following 2015, interest rates gradually increase until 2020 and, by following the convention of Rogers et al. (2014), QE becomes more effective over time which is reflected by the slight trend in increased correlation as well as the stagnation in TSMOM. In the remaining period leading up to 2022, the FED implemented the latest, and most substantial, round of QE as a response to the emergence of Covid-19. At the same time, short-term interest rates drop to zero, where near-zero interest rates persist throughout the sample. Even with the significant increase in QE, it is evident the near-zero interest rates prevents a substantial increase in correlation. Overall, considering the whole post QE period, this salient stagnation in TSMOM return and the increase in correlation effectively imply a dissipation in the precedent diversification benefits.

Our findings are further corroborated by evaluating the TSMOM performance in the presence of QE, which results are presented in Table 8. Interestingly, QE does not have a direct negative effect on TSMOM, but rather a significant positive effect. Intuitively, this may be perceived as an anomaly given our preceding argumentation and findings, whereas one might expect a negative relation between the two. However, this may be explained by a combination of the overall economic growth induced by the policy, represented by the positive coefficients, and the indication of indirect causation through ripple effects in the market. The negative effect from QE is rather incorporated in the alpha of the strategy, which is shown by the negative intercept in column two of Table 8. The implication of a negative alpha signifies a reversal in the intercept, i.e., the strategy actively generates a return below that of the market, however insignificant. From the sign of the intercept, we get a clear indication, in the presence of QE, the TSMOM strategy loses its edge. In fact, QE indirectly causes the strategy to impede itself by actively reducing the portfolio return as a result of wrongfully predicting future prices as well as the inability to secure benefits through diversification. This proves to be the case for both the diversified portfolio and each asset class, besides from bonds (FI) which accordingly has an R^2 of 0%.

Compared to the corresponding results in Tables 2 and 3 (monthly), the inclusion of QE leads to an overall slight increase in the R^2 giving a more accurate representation of the variation in TSMOM, which is substantiated by the significance exhibited by ΔQE on TSMOM in Table 8. This implies a significant portion of the gross return on TSMOM is actually explained by the change in QE. Most likely, this manifestation occurs in the periods with near-zero short-term interest rates, when there is less correlation and more distinct diversification benefits, facilitating the portfolio to partake in the overall market upturn induced by QE.

Table 8

Regression summary: TSMOM on quantitative easing (Equations 14, 15, 16, and 17)
Sample: December 2009 – December 2021

	Intercept	*MSCI*	*BOND*	*GSCI*	*SMB*	*HML*	*UMD*	*VAL*	*MOM*	ΔQE	R^2
TSMOM *ALL*	-0.14% (-0.37)									0.28 * (2.53)	4%
TSMOM *COM*	-0.10% (-0.24)									0.36 ** (2.96)	6%
TSMOM *EQ*	-0.24% (-0.34)									0.05 (0.23)	0%
TSMOM *FI*	0.45% (0.79)									0.08 (0.47)	0%
TSMOM *FX*	-0.89% (-1.42)									0.56 ** (3.12)	6%
TSMOM *ALL*	-0.11% (-0.27)	0.06 (0.49)	-0.14 (-0.29)	-0.13 (-1.49)	-0.02 (-0.12)	0.20 (1.19)	0.05 (0.41)			0.28 * (2.32)	7%
TSMOM *ALL*	-0.15% (-0.38)	-0.04 (-0.45)			-0.06 (-0.39)	0.19 (1.22)	0.08 (0.61)			0.31 ** (2.73)	6%
TSMOM *ALL*	-0.12% (-0.30)	-0.07 (-0.73)						0.17 (0.58)	0.06 (0.21)	0.29 * (2.56)	5%

6 Conclusion

In wake of the financial crisis, the market sustained severe consequences followed by a period accommodating quantitative easing, sub-periods with both low- and near-zero- interest rates, increased liquidity, and elevated prices. Historically, time series momentum is hypothesized to display virtues performance during extreme market conditions and prevail as a trend following strategy. However, we document a vast reduction in price predictability, diversification benefits and overall performance of the TSMOM strategy in the presence of QE, with hardly any evidence of time series momentum as a factor being present in our sample. Initially, QE has a positive effect on both the return on the TSMOM portfolio and on the correlation between assets. The increased correlation leads more coordinated movement amongst assets (in the same or opposite direction), meaning there is considerably fewer independent trends in the market. For a trend following strategy such as time series momentum, this implies a loss of diversification benefits from investing across assets. Additionally, the high correlation and elevated prices induced by QE to promote economic growth may be responsible for the reduction in the asset's dependency on its own previous prices, explaining the poor price predictability as well as the absence of time series momentum as a factor. Ultimately, QE has an indirect negative effect on time series momentum through ripple effects in the market, impairing the proclaimed robustness of the strategy. Consequently, a time series momentum strategy is incapable of generating a significant alpha and hence unviable given the current market conditions.

Following the closure of 2021, we immediately experience rapidly increasing interest rates coinciding with the highest inflation rate seen since the early 1980s. With the FED's most recent decision to commence unwinding their QE positions, the imminent state of the market may in fact prove beneficial for time series momentum strategies. With these prospects in mind, we recommend extending our research by exploring the forthcoming resurgence of time series momentum within the conceivable extreme market conditions. Additionally, with more information and documentation on the exhaustive economic effect of QE, it would be interesting to see comprehensive research conducted on the expanded long-term implications on time series momentum. Other plausible extensions include examining time series momentum strategies held over different horizons and scaling the assets' position by relative weighted volatility as opposed to 40% fixed volatility.

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8 Appendix

Appendix A

Summary statistics on futures contracts

Initial summary statistics for direct comparison against Moskowitz et al. (2012)

Sample: December 2009 – December 2021

	Annualized mean return	*Annualized volatility*	*Avg. net speculator long position*	*Std. dev. net speculator long position*
Commodity Futures				
ALUMINUM	3.90%	19.96%		
BRENTOIL	6.22%	35.20%		
CATTLE	5.78%	18.63%	8.45%	10.20%
COCOA	1.45%	26.52%	5.15%	14.36%
COFFEE	9.10%	31.72%	7.06%	14.01%
COPPER	4.71%	21.73%		
CORN	6.70%	27.24%	7.49%	11.52%
COTTON	6.80%	26.56%	-0.81%	20.01%
CRUDE	-22.25%	103.07%	1.25%	5.74%
GASOIL	4.95%	30.19%		
GOLD	5.48%	16.05%	8.17%	24.16%
HEATOIL	5.75%	31.30%	2.80%	6.44%
HOGS	6.16%	29.68%	5.11	14.33
NATGAS	7.68%	47.36%	-1.74%	8.74%
NICKEL	5.09%	29.15%		
PLATINUM	-0.55%	23.53%		
SILVER	7.35%	30.41%	22.76%	14.60%
SOYBEANS	4.26%	21.10%	8.58%	31.31%
SOYMEAL	5.74%	26.64%	7.34%	11.64%
SOYOIL	5.05%	20.81%	6.45%	13.34%
SUGAR	2.10%	31.60%	9.49%	14.65%
UNLEADED	9.09%	40.55%	9.96%	9.54%
WHEAT	7.14%	29.44%	3.74%	12.54%
ZINC	6.03%	25.34%		
Bond Futures				
2-year EURO	-0.77%	8.56%		
5-year EURO	-0.24%	8.68%		
10-year EURO	1.57%	9.57%		
30-year EURO	6.69%	14.19%		
10-year CAN	0.32%	8.70%		
10-year JP	-1.54%	10.54%		
10-year UK	-0.49%	10.82%		
2-year US	0.38%	1.95%	1.81%	12.00%
5-year US	0.07%	4.40%	2.56%	9.03%
10-year US	0.15%	6.22%	0.93%	7.71%
30-year US	2.04%	10.56%	-1.38%	6.37%
Currency Forwards				
AUD/USD	-2.39%	10.85%	12.51%	27.73%
EUR/USD	-1.27%	8.73%	11.92%	19.10%
CAD/USD	1.52%	8.06%	3.90%	23.83%

JPY/USD	2.54%	8.94%	-6.94%	23.92%
NOK/USD	3.18%	11.96%		
NZD/USD	0.40%	11.29%	33.08%	33.16%
SEK/USD	2.41%	10.81%		
CHF/USD	-1.70%	10.68%	-7.24%	27.48%
GBP/USD	-0.26%	9.04%	2.50%	25.60%
Equity Index Futures				
ASX SPI 200 (AUS)	3.95%	20.67%		
DAX (GER)	8.42%	21.99%		
IBEX 35 (ESP)	-1.15%	25.70%		
CAC 40 10 (FR)	5.52%	22.68%		
FTSE/MIB (IT)	2.84%	26.25%		
TOPIX (JP)	6.47%	19.18%		
AEX (NL)	7.09%	19.81%		
FTSE 100 (UK)	2.96%	18.98%		
S&P 500 (US)	13.08%	16.89%	-4.14%	5.13%

Appendix B

t-statistic of alpha (intercept) from regressing time series momentum strategy $(k, 1)$ on market proxies and FF factors in consolidation with various look-back periods (Equation 5)

Sample period: December 1984 – December 2021

Look-back period	*1*	*3*	*6*	*9*	*12*	*24*	*36*	*48*
All assets	2.10 *	2.17 *	1.76 (*)	0.97	2.75 **	0.87	-0.96	-1.59
Commodity	-0.18	0.81	-0.59	-2.31 *	1.45	0.20	-1.98 *	-1.31
Equity	1.36	2.12 *	2.95 **	3.82 ***	3.48 ***	3.33***	1.90 (*)	2.55 *
Bond	3.10 **	1.72 (*)	1.57	1.14	1.64	-0.56	-0.57	-1.85 (*)
Currency	2.03 *	1.25	1.94 (*)	1.45	1.21	0.03	0.00	-1.57

Appendix C

Regression summary: Diversified TSMOM on MSCI World and FF factors (Equation 8)

Sample period: December 1984 – December 2021

		Intercept	*MSCI*	*SMB*	*HML*	*UMD*	R^2
Monthly	*Coefficient* *(t-stat)*	0.63% (3.16 **)	0.01 (0.20)	-0.04 (-0.61)	-0.01 (-0.16)	0.07 (1.59)	0.8%
Quarterly	*Coefficient* *(t-stat)*	1.49% (2.32 *)	0.03 (0.44)	-0.08 (-0.59)	0.02 (0.22)	0.24 (2.85 **)	7%

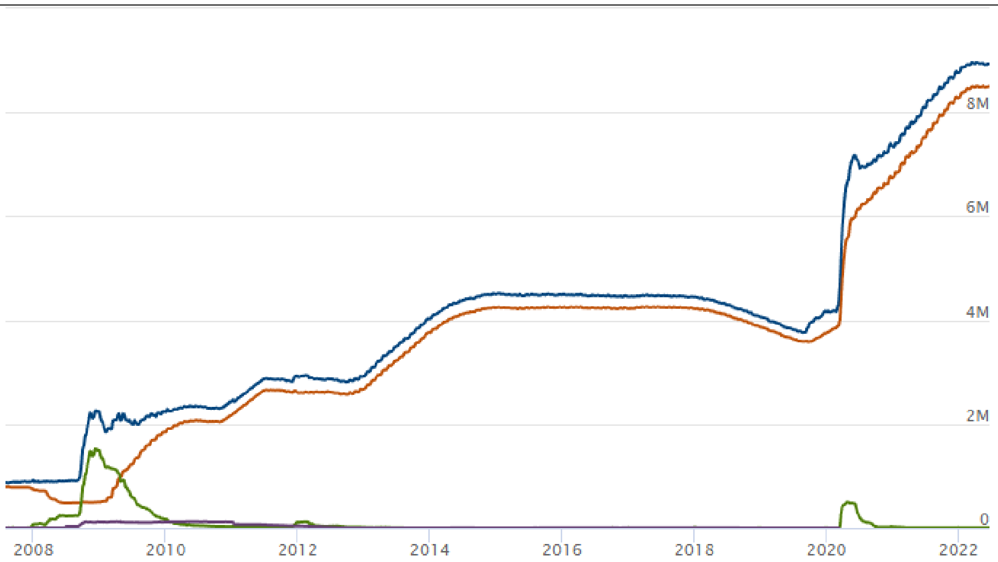
Appendix D

Regression summary: TSMOM on MSCI World and value and momentum "everywhere" factors (Equation 9)
Sample: December 1984 – December 2021

		Intercept	*MSCI*	*VAL*	*MOM*	R^2
Monthly	*Coefficient* *(t-stat)*	0.59% (2.86 **)	0.00 (0.09)	0.08 (0.55)	0.21 (1.64)	0.7%
Quarterly	*Coefficient* *(t-stat)*	1.39% (2.06 *)	-0.00 (-0.01)	-0.01 (-0.06)	0.61 (3.06 **)	10%

Appendix E

Progressive change in FED's balance sheet
Sample: July 2008 – June 2022
Source: Board of Governors of the Financial System (2022c)



- Total Assets (in millions of dollars)
- Securities Held Outright (in millions of dollars)
- All Liquidity Facilities (in millions of dollars)
- Support for Specific Institutions (in millions of dollars)