The Trend is Your Friend: Time-series Momentum Strategies across Equity and Commodity Markets

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Abstract

Using a dataset of 67 equity and commodity indices from 1969 to 2013, this study documents a significant time-series momentum effect across international equity and commodity markets. This paper further documents that international mutual funds have a tendency to buy instruments that have been performing well in recent months, but they do not systematically sell those that have been performing poorly in the same periods. We also find that a diversified long-short momentum portfolio realizes its largest profits in extreme market conditions, but the market interventions by central banks in recent years seem to challenge the performance of such portfolios.

JEL classification: G12, G13, G15, G23, G11

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"Over time, value is roughly the way the market prices stocks, but over the short term, which sometimes can be as long as two or three years, there are periods when it doesn't work. And that is a very good thing."

— Jack D. Schwager

1. Introduction

The momentum anomaly can be encountered in two dimensions: cross-sectional and time-series. According to the traditional and well-documented idea of cross-sectional momentum, instruments that outperform their peers in a three- to twelve-month period tend to do so also over the next year.[3] A newer version of the momentum anomaly refers to time-series momentum, which focuses on an instrument's absolute performance. In particular, according to the time-series momentum perspective, an asset's past performance predicts its future performance, emphasizing the crucial role of autocorrelation in returns. Moskowitz, Ooi and Pedersen (2012) are the first to provide evidence of the existence of time-series momentum with respect to *futures* markets. They find that excess return during the preceding 12-month period of a futures contract is a positive predictor of its future return during the next year, and that a diversified portfolio that buys instruments that have been in an uptrend and sells those that have been in a downtrend delivers substantial abnormal returns.[4]

Recent studies on time-series momentum have focused primarily on futures markets and managed futures funds (e.g., Baltas and Kosowski, 2012; Moskowitz et al., 2013). Given that more than 9.5 trillion U.S. dollars in assets are estimated to be benchmarked to global equity (i.e. MSCI indexes) and commodity indexes (i.e. S&P GSCI) by the end of 2013, and the increasing number of international mutual funds and Exchange Traded Funds (ETFs), the academic literature has surprisingly devoted little attention to trend following and time-series momentum effects among conventional asset classes.[5] This study contributes to the existing literature by providing new insights into the existence of time-series momentum across global equity and commodity indices, as well as its explanatory power on the performance of

[3] Extensive studies have provided evidence of the cross-sectional momentum profitability for several decades (e.g., Jegadeesh and Titman, 1993; Asness 1994, Grundy and Martin, 2001; Griffin, Ji, and Martin, 2003, 2005); and across various asset classes and countries (e.g., Asness, Liew, and Stevens, 1997; Rouwenhorst, 1998; Moskowitz and Grinblatt, 1999; Bhojraj and Swaminathan, 2006; Erb and Harvey, 2006; Gorton, Hayashi, and Rouwenhorst, 2008; Garleanu and Pedersen, 2009; DeMiguel, Nogales, and Uppal, 2010; and Asness, Moskowitz and Pedersen, 2013).

[4] Baltas and Koswiki (2013) confirm the profitability of time-series momentum strategies in global futures markets, and further show that time-series momentum strategies explain a significant part of hedge fund returns. Menkhoff, Sarno, Schmeling, and Schrimpf (2012), however, find that cross-sectional momentum outperforms time-series in the current market.

[5] MSCI stands for Morgan Stanley Capital Indexes. GSCI stands for Goldman Sachs Commodity Indexes. The number is available at www.msci.com/indexes.

international mutual funds. Indeed, we show that trends in the most traditional instruments such as equity and commodity indices are consistent and even stronger than trends in futures markets, and that trend-following strategies for these instruments are highly profitable. Interestingly, the addition of recent years to the present dataset permits an investigation of time-series momentum in light of central bank intervention, which is known to have distorted correlations across asset classes.

Over the years, trend-following strategies have become one of the most important investment strategies in the hedge fund universe. For instance, Moskowitz et al. (2012), Baltas and Kosowski (2013), and Hurst, Ooi, and Pedersen (2014) document that a substantial part of the hedge fund industry, such as Managed Futures Funds and Commodity Trading Advisors (CTAs), follows time-series momentum strategies. We extend this line of research by examining whether particular strategies can be associated with other types of institutional investors, i.e. international mutual funds, which can be characterized as more traditional and risk-averse, or whether they strictly concern the hedge fund industry.

We find that the time-series momentum trading strategy explains a significant proportion of international mutual fund performance.[6] Specifically, international mutual funds have proven to be time-series momentum investors, implying that they tend to buy instruments that have been in an uptrend and sell those that have been in a downtrend. However, while time-series momentum can only partially capture mutual fund performance, a long-only portfolio that invests in instruments that have been performing well or that are in risk-free assets may entirely capture mutual fund behaviour. Therefore, it is likely that mutual funds will show an investment preference for long-only trend-following strategies. These findings are consistent and robust across all samples of asset classes and mutual funds examined. Moreover, they complement existing literature on cross-sectional momentum (e.g. Grinblatt, Titman, Wermers, 1995), where there is evidence that mutual funds have a tendency to buy winners, but they do not systematically sell losers.

We first document the existence of strong return autocorrelation across equity and commodity indices. In particular, we show that the excess return over the past 12 months positively predicts the excess return for the next year. Subsequently, the detected return continuation dissipates or exhibits reversals. These findings confirm behavioural theories of initial under-reaction and delayed over-reaction by investors (Barberis, Shleifer, and Vishny

[6] For example, Cumby and Glen (1990) examine the risk-adjusted performance of international mutual funds, while Goetzmann, Ivkovic, and Rowenhourst (2001) and Chua, Lai, and Wu (2008) investigate their fair pricing.

1998; Daniel, Hirshleifer, and Subrahmanyam 1998; Hong and Stein 1999). Furthermore, the presence of return autocorrelation seems to challenge the weak form of the efficient market hypothesis, according to which future performance cannot be predicted by information contained in historical prices.

Following the strong evidence of return predictability, we further construct time-series momentum strategies over a number of look-back and holding periods. We find that time-series momentum strategies deliver substantial abnormal returns with respectable Sharpe ratios for horizons of up to one year. Over longer horizons, the time-series momentum effect dissipates or reverses, as in the case of cross-sectional momentum and return continuations. These results are consistent and robust across all asset classes, subsamples, combinations of look-back and holding periods, and different sample periods.

We further show that time-series momentum strategies tend to outperform cross-sectional momentum strategies, and this finding becomes stronger over shorter holding periods. To better investigate the abnormal performance of time-series momentum, the single and diversified across assets 12-1 time-series momentum strategy is evaluated with regard to standard asset pricing models. Remarkably, the 12-1 strategy cannot be explained by any of the size, value, or growth factors examined, nor by market or commodity benchmarks, but can be partially captured by cross-sectional momentum factors such as Fama and French's UMD (*Up-minus-down*) factor and Asness, Moskowitz, and Pedersen's MOM (*Momentum*) factor. The relationship between time-series and cross-sectional momentum is further investigated, and it is found that these two investment philosophies are indeed highly related, but distinct from each other in their statistically significant alpha coefficients.

We also document substantial evidence that time-series momentum serves as a hedging strategy in all examined asset classes, and that its payoffs resemble those of an option straddle, which is consistent with Moskowitz et al. (2013). More precisely, it is found that time-series momentum experiences its highest gains during extreme market movements in either direction, rendering explanations of its high profitability even more puzzling from a risk-adjusted perspective. However, this study casts doubt on the future of time-series momentum profitability since the aggressive monetary policies adopted by central banks have increased correlations across asset classes. As a consequence, there are fewer independent trends from which time-series momentum can benefit.

The rest of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the dataset and the methodology used for constructing momentum strategies. Section 4 presents the results of time series momentum trading strategies, while

Section 5 presents evidence that international mutual funds' performance is closely related to time series momentum trading strategies. Section 6 describes robustness checks in different sample periods and extreme market conditions. Section 7 concludes.

2. Related Literature

2.1. Evidence for Time-Series Momentum

In 2012, Moskowitz, Ooi and Pedersen provided alternative evidence to the momentum phenomenon, focusing on what they called "time-series momentum." They describe time-series momentum as an asset-pricing anomaly in which an instrument's past return is positively correlated with its future return over a period of 1 to 12 months. This suggests that one could generate higher returns simply by using long instruments with recent positive returns and going short for those with recent negative returns. Moskowitz et al. (2012) examine this trend-following phenomenon for 58 futures and forward contracts from various asset classes and find that it persists in each of the contracts they study. They also note that returns generated by time-series momentum strategies partially reverse over longer horizons, supporting behavioral explanations of initial under-reaction and delayed over-reaction.

Moskowitz et al. (2012) note that time-series momentum is related to but distinct from the classic cross-sectional momentum of Jegadeesh and Titman (1993). In order to investigate this, they decompose returns into time-series and cross-sectional momentum strategies, and find that lead-lag effects that contribute to cross-sectional momentum are not apparent in the case of time-series momentum and that futures contracts returns have a positive auto-covariance in common. Based on this finding they conclude that time-series momentum can capture some features of cross-sectional momentum.

Interestingly, they also note that superior returns associated with this trend effect are not due to risk compensation since a time-series momentum strategy performs best during extreme markets. As a result, their time-series momentum trading strategies exhibit no relationship with risk factors such as HML and SMB, but seem to be partially explained by momentum factors, supporting once again a relationship with cross-sectional momentum.

Moskowtiz et al. (2012) attempt to establish a relationship between the positions of hedgers and speculators, as well as a relationship between hedge funds returns and time-series momentum strategies themselves. Interestingly, they find that speculators and hedgers engage in time-series momentum strategies, permitting the former to profit at the expense of the latter. As far as hedge fund investment behavior is concerned, they find that hedge fund returns can be explained by these trend-following strategies.

2.2. Time-Series Momentum and the Performance of Managed Futures Funds

After the work of Moskowitz, Ooi and Pedersan (2012) was first released, several studies followed focusing primarily on the source of profitability generated by managed futures funds and CTAs, which together constitute a substantial part of the hedge fund industry. In particular, Hurst, Ooi, and Pedersen (2012) observe that trend-following strategies such as time-series momentum can explain managed futures' returns. Remarkably, they demonstrate that when they control for time-series momentum strategies, excess returns (or alphas) cannot be attributed to other long-only benchmarks. In addition, they also highlight the relative importance of the horizon of these strategies as well as the asset classes that may be concerned. They find that most managed futures funds are focused on medium- and long-term trends, due to lower transaction costs, as well as on fixed income due to its higher liquidity.

In another paper, Hurst, Ooi and Pedersen (2014) provide evidence for a whole century of strong performance of time-series momentum strategies, extending the evidence provided by Moskowitz et al. (2012). Moreover, the authors express their concern about the outlook of time-series momentum strategies in light of their recent drawdowns. Specifically, they claim that the current economic environment, with central banks intervening in the market, not only distorts existing trend patterns, but also leads to increased correlations across futures markets. Therefore, the diversification benefit previously afforded to momentum strategies has been substantially reduced since there are fewer independent trend patterns that can be exploited. However, even in this case the authors state that managed futures funds could benefit from emerging equity and currency markets, which are much more liquid than in the past.

Baltas and Kosowski (2012) are also concerned with the relationship between time-series momentum strategies in futures markets and CTAs, and once again they provide strong evidence that CTAs follow time-series momentum. In order to better approximate CTA strategies, they examine higher frequencies such as weekly and daily ones, thereby extending the approach of Moskowitz et al. (2012). Interestingly, they document that strategies at different frequencies exhibit low correlations with one another, and therefore reflect distinct continuation phenomena. Additionally, they note that CTAs have been performing poorly recently and for this purpose they consider capacity constraints as a possible reason for this underperformance. However, their results indicate that there are no significant capacity constraints on momentum strategies, which is consistent with the view that futures markets are liquid, but it renders the reason for the underperformance of CTAs unclear.

3. Data and Preliminaries

This study examines the existence of time-series momentum across equity and commodity markets. The present dataset consists of monthly closing prices for 45 equity indices covering developed and emerging markets and 22 commodity indices — in total 67 different instruments — from December 1969 through December 2013. All instrument prices are denominated in U.S. dollars, since this study is conducted from a U.S. perspective. In addition, the dataset includes monthly returns for international, global, and commodity mutual funds, which are examined in order to establish a link between time-series momentum and mutual fund behavior.

3.1. International Equity Indices

The dataset for equity indices is obtained from Bloomberg and consists of monthly closing prices for 45 Morgan Stanley Capital International (MSCI) indices across 23 developed and 22 emerging countries. Price data for equity indices date back to December 1969 or later. The MSCI indices considered are free float-adjusted market capitalization weighted indices that replicate the equity market performance of developed and emerging countries (MSCI, 2014). Given that all of the MSCI indices represent mainly large capitalization and liquid stocks, potential biases due to illiquidity and non-synchronous trading are eliminated.

3.2. Commodity Indices

The dataset for commodity indices consists of 22 commodity indices, which are obtained from Bloomberg and date back to December 1969. The dataset is based on the Goldman Sachs Commodity Index (S&P GSCI), which is designed to track an unleveraged and long-only investment in commodity futures, and is diversified across individual commodity components (S&P GSCI, 2014). The commodity indices are weighted to account for economic significance as well as market liquidity. It is important to highlight that when it comes to returns, excess return indices were considered instead of total returns indices to take into account the effect of contango and normal backwardation in these markets.

[Insert Table 1 here]

Table 1 presents some descriptive statistics for all instruments considered in the present dataset with regard to the beginning of a time-series of data, annualized mean and volatility, and skewness and kurtosis. Looking at these quantities of interest, one can observe that there is a substantial variation in the annualized mean returns across assets, with equity indices generating primarily positive returns, while many commodity indices yield negative returns over the sample period.

As far as the annualized volatilities are concerned, many extreme observations that are even higher than 100% can be noted, especially in emerging and commodity markets. However, in contrast to Moskowitz et al. (2012) and Baltas and Kosowski (2012), volatilities across asset classes and instruments are more homogeneous and have fewer striking differences. This is due to the fact that the present dataset does not include currency or bond markets. Finally, the dataset demonstrates reasonable levels of skewness and kurtosis.

3.3. Mutual Funds

Mutual Fund data are obtained from the CRSP Survivor-Bias-Free US Mutual Fund Database and cover the period December 1969 through December 2013. In order to represent the various asset classes and markets, which are considered as closely as possible, the mutual fund dataset is limited to international and global equity funds, and commodity funds. The data used for global and international equity funds begins in December 1969, while that for commodity funds begins in April 1997. The funds are classified according to the Lipper Objective Codes and only funds with no sales restrictions are included in the dataset. When it comes to mutual fund asset decomposition, only funds investing at least 60% of their capital in equity and commodity instruments are considered. For the remaining dataset, monthly total returns, calculated as the change in NAV,[7] were considered for each fund. The final sample contained 454 international, global, and commodity mutual funds at the end of 2013.

3.4. Time-Series Return Predictability

Given that time-series momentum strategies are considered to be trend-following strategies, it is of great importance to detect price continuation patterns before implementing them. Price continuation patterns would signify return predictability, and that would further suggest that a time-series momentum strategy can generate substantial profits. For this purpose and similarly to Moskowitz et al. (2012), the price continuation is examined across

[7] Net Asset Values are net of all management expenses as well as 12b-fees.

all instruments combined, by regressing the excess return[8] for instrument j in month t on its own return lagged h months. Thus, the pooled panel linear regression can be estimated as follows:

$$\boldsymbol{r_t^j = a + \beta_h r_{t-h}^j + \varepsilon_t} \tag{3.1}$$

where r_t^j is the excess return of instrument j in month t and r_{t-h}^j is the excess return of instrument j in month t lagged h months. The regression, defined in equation (3.1), is a pooled panel regression in which all instruments (67 in total) and dates are combined to generate the beta coefficients. The number of lags for each instrument extends to 60 months (h=1, 2,…, 60), and thus 60 regressions are estimated. It is important to highlight that in the present dataset there is no substantial variation in volatilities, and for this reason there is no need to scale the excess returns by their *ex-ante* volatilities, as in the case of Moskowitz et al. (2012) and Baltas and Kosowski (2012). In this regression, the quantity of interest is the t-statistic, where a significant t-statistic indicates the existence of time-series return predictability. Specifically, a positive t-statistic signifies return continuation, whereas a negative t-statistic signifies a reversal.

[Insert Figure 1 here]

Figure 1 presents the t-statistics of the beta coefficients with regard to the pooled panel regression, for lags h=1,2,…,60. When asset classes are examined at an aggregate level (Panel A), it can be noted that the t-statistics in all of the first 12 lagged months are positive and significant. Over longer horizons (13 to 60 lags) the t-statistics deliver lower positive values and in some cases significantly negative values. These results indicate the existence of a return continuation for the first year that subsequently gives rise to weaker reversals. As a result, the hypothesis for time-series return predictability can be confirmed. This implies that past returns are able to predict future returns and that trend-following patterns are thereby created.

These findings are consistent with those documented by Moskowitz et al. (2012) and Baltas and Kosowski (2012) with respect to return continuations and reversals in futures markets. Nonetheless, in the present case the return continuation seems to be more persistent given some positive spikes at lags greater than 12. Apart from that, reversals in returns generate weaker signals than those reported by Moskowitz et al. (2012). Baltas and Kosowski (2012) are also unable to show strong reversals over longer horizons, arguing that this result

[8] Data on the three-month Treasury bill is obtained from Bloomberg and is used to represent the risk-free rate.

is due to the use of a larger sample in both time-series and cross-sectional dimensions. This rationale can also be inferred from our present study, where the dataset starts in 1969 and consists of 67 instruments.

As far as asset classes are concerned, the return predictability seems to be slightly stronger in the case of equity versus commodity indices. In the case of equity indices, 11 out of 12 lags are positive and significant, whereas only seven out of 12 lags are positive and significant for commodity indices. Also, the return continuation tends to be more persistent and decays to a smaller extent for equity indices. Hence, it is expected that time-series momentum strategies will be more profitable for equity than for commodity indices.

4. Empirical Evidence

4.1. Time-Series Momentum Strategies

In the previous section (3.4), the positive correlation between past return and future returns suggested the existence of trend-following patterns. Therefore, it is reasonable to construct time-series momentum strategies that take advantage of these patterns, and to evaluate their profitability.

Before analyzing the methodology for constructing time-series momentum strategies, it is of great importance to highlight that these strategies can be constructed based on different time horizons. Thus, it is essential to define the periods involved in constructing time-series momentum strategies: the look-back or formation period and the holding period. The look-back period J refers to the number of lagged months in which returns are examined to form the momentum portfolio, while the holding period K refers to the number of months that the momentum portfolio is held or active after it is formed. K and J can vary through time, allowing for different combinations between the look-back and holding periods. Therefore, a 12-1 strategy, where 12 indicates the look-back period J and 1 the holding period K, refers to a portfolio that is constructed based on the instrument returns over the past 12 months, and held for one month after its formation.

As in Moskowitz et al. (2012), Baltas et al. (2012), and Hurst et al. (2012), a time-series momentum strategy takes a long (short) position for a single instrument when the sign of its cumulative return over a particular look-back period is positive (negative). The trading sign takes the value 1 when the cumulative return of the asset over the look-back period J is positive and the value -1 otherwise. The time-series momentum return of each instrument is calculated based on the trading sign and the return over the holding period. Moreover, similarly to Jegadeesh and Titman (1993), one month is skipped between the formation and holding periods, to avoid some of the bid-ask spread, price pressure, and lagged reaction effects (Jegadeesh, 1990; Lehmann, 1990). Subsequently, time-series momentum returns are aggregated to form the momentum portfolios as follows:

$$\boldsymbol{P_J^K = \frac{1}{N_t}\sum_{i=1}^{N_t} signal_j\,(cumr_{t-J,t}^{j})r_{t,t+K}^{j}} \tag{3.2}$$

where N_t indicates the number of available instruments at time *t*, P_J^K is the return on the time-series momentum portfolio with a look-back period of *J* months and holding period of *K* months, $signal_j$ takes the value 1 (-1) if the cumulative return $cumr_{t-J,t}^{j}$ in month *t* for instrument *j* over the past *J* months is positive (negative), and $r_{t,t+K}^{j}$ is the return with respect to a holding period of *K* months.

[Insert Table 2 here]

Table 2 depicts the annualized mean returns alongside their Sharpe ratios generated by time-series momentum strategies over a number of look-back and holding periods. Panels A, B, and C present these quantities for all asset classes, and equity and commodity indices, respectively. The annualized mean returns of time-series momentum strategies are positive and statistically different from zero with respect to time horizons of up to one year. Over longer horizons, time-series momentum strategies deliver lower returns that are not significant or even negative (for commodity indices, Panel C). These findings confirm the price continuation patterns detected in the previous section, as well as results documented in the time-series momentum literature. Thus, it can be concluded that apart from the case of futures markets, time-series momentum can be successfully applied to a more traditional range of instruments, such as equity and commodity indices. Moreover, the particular strategies seem to yield a respectable 0.70 Sharpe ratio when applied for up to one year. Time-series momentum strategies can also be successfully applied to individual stocks. However, further investigation of individual stocks is beyond the scope of this study.

Taking a closer look at Panels B and C, where each asset class is examined separately, it can be observed that time-series momentum profitability is slightly more pronounced across equity indices than commodity indices. More precisely, time-series momentum delivers returns in the range of 2% to 17% with regard to equity markets, and 2% to 11% with regard to commodity markets. The higher momentum profitability of equity indices is further supported by noticing their respective Sharpe ratios, which seem superior in equity markets.

These findings confirm the predictability patterns observed in the previous section, where return continuations proved to be stronger for equity indices. Surprisingly, reversal patterns in time-series momentum returns are observed only for commodity indices, while as far as equity indices are concerned, only weaker positive returns are noted. This might also be the reason why, when the aggregate strategy is examined, similar behavior can be observed. Once again, these findings are in line with those reported by Baltas and Kosowski (2012), who could not find strong reversals over longer horizons. Therefore, adopting the arguments of Baltas and Kosowski (2012), this paper suggests that the use of a larger sample both for time-series and cross-sectional analysis provides one reason why strong reversals are not noted.

In order to investigate further time-series momentum across equity markets, equity indices are distinguished for developed and emerging markets. This will allow examining whether time-series momentum patterns are similar in these two different types of market.

[Insert Table 3 here]

Remarkably, Table 3 provides evidence on the different behavior of time-series momentum with respect to developed and emerging markets. In particular, it can be noted that emerging markets experience much higher time-series momentum returns compared to developed markets. However, the time-series momentum phenomenon is of far shorter duration in the case of emerging markets. Indeed, the profitability of these strategies is significant up to nine months only and then starts to dissipate, whereas the standard strategy of a look-back period of 12 months and a holding period of 1 month does not deliver substantial abnormal returns.

4.2. Cross-Sectional Momentum Strategies

The existing literature finds a significant relationship between time-series and cross-sectional momentum, as well as that the former outperforms the latter most of the time. This section aims to investigate the profitability of cross-sectional momentum strategies applied to equity and commodity markets, and to compare it to time-series momentum profitability. The relationship between cross-sectional and time-series momentum is examined further in section 4.4.

Moskowitz et al. (2012) document a significant relationship between cross-sectional and time-series momentum strategies, finding that cross-sectional momentum cannot entirely capture time-series momentum. Antonacci (2013) reaches the same conclusions and further documents the out-performance of time-series momentum strategies compared to cross-sectional momentum strategies, as documented by Jegadeesh and Titman (1993). For this purpose, it is of great importance to examine cross-sectional momentum strategies applied to the present dataset and report whether the findings documented in the momentum literature are supported by the present study.

The methodology for constructing cross-sectional momentum portfolios follows that of Jegadeesh and Titman (1993). To recap, at the beginning of each month they rank stocks from highest to lowest based on their returns over various past periods. Subsequently, they divide these stocks into equally-weighted decile portfolios so that the stocks with the highest past returns are allocated to one portfolio, those with the second highest past returns are allocated to another portfolio, and so on. Then, they hold these portfolios for a given period of time, observing their holding period returns. Based on these returns, Jegadeesh and Titman (1993) are able to determine whether stocks that performed well or poorly in the past will continue to do so in the future.

We follow a similar philosophy for constructing cross-sectional momentum strategies. However, instead of sorting instruments into 10 equally-weighted portfolios, quintile portfolios were considered since the present dataset deals with a smaller number of instruments. Moreover, as in the case of time-series momentum, and similarly to Jegadeesh and Titman (1993), one month is skipped between the formation and holding periods.

[Insert Table 4 here]

Table 4 presents the annualized mean returns generated by cross-sectional momentum strategies, allowing for a variety of look-back and holding periods. It can be noted that buying winners and selling losers yields significant profits. However, cross-sectional momentum profitability is stronger for the equity index than for the commodity index and the most profitable results are noted when the two asset classes are combined. Moreover, all asset classes seem to exhibit reversals in their cross-sectional momentum returns after one year. Similar to Antonacci (2013), time-series momentum strategies out-perform relative strength strategies when examined in all three cases, and especially when looking at a holding period of one month. Remarkably over longer holding periods, cross-sectional momentum strategies seem to deliver higher annualized mean returns, but this result is only marginal.

4.3. Evaluating Time-Series Momentum Strategies

Following the significant time-series momentum profitability observed in section 4.1, this section aims to further investigate the abnormal performance of time-series momentum by estimating some standard asset pricing models as defined in equation 3.3. Specifically, the single diversified-across-assets 12-1 time-series momentum strategy is investigated since, as already mentioned, it serves as a benchmark in the existing literature.

To better investigate the performance of time-series momentum strategies, we regress time-series momentum returns on a number of factors. This allows for better evaluation of the drivers of time-series momentum profitability. Attention is drawn to the single diversified[9] 12-1 time-series momentum strategy, which serves as the benchmark in the momentum literature and refers to a strategy with a look-back period of 12 months and a holding period of 1 month. The specified model can be estimated as follows:

$$\boldsymbol{TSMOM_{t,i}^{(12,1)} = \alpha + \beta_1 MSCI_t + \beta_2 GSCI_t + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 UMD_t + \varepsilon_t} \quad \textbf{(3.3)}$$

where $TSMOM_{i,t}^{(12,1)}$ is the equally-weighted average return across instruments of the single diversified time-series momentum strategy in month *t* for asset class *i*, with a look-back period of 12 months and a holding period of 1 month, $MSCI_t$ is the return of the MSCI World Index in month *t,* $GSCI_t$ is the return of the S&P GSCI in month *t*, and the SMB, HML, and UMD regressors are Fama-French factors representing size, value, and momentum across U.S. stocks, respectively.

Given that the present dataset concerns instruments from different asset classes and markets, the strategy is further regressed on alternative factors, including "momentum everywhere" factors from Asness et al. (2013), and as such it better resembles the present dataset. These factors replace the Fama-French factors, which are limited to U.S. stocks. However, since the present dataset excludes foreign exchange markets as well as bond markets, the "momentum everywhere" factors are adjusted to reflect this change, and to represent the dataset as closely as possible. Thus, the specified model can be written as:

$$\boldsymbol{TSMOM_{t,i}^{(12,1)} = \alpha + \beta_1 MSCI_t + \beta_2 GSCI_t + \beta_3 VAL_t + \beta_4 MOM_t + \varepsilon_t} \quad \textbf{(3.4)}$$

where the first two regressors remain the same, while VAL and MOM represent value and momentum, respectively, and replace the Fama-French three-factor model.

[9] In this study, "diversified returns" refers to equally-weighted average returns across all instruments.

[Insert Table 5 about here]

Table 5 reports the risk-adjusted performance of the single diversified 12-1 time-series momentum strategy. It can be observed that the strategy delivers large and significant alphas in all asset classes, indicating its out-performance relative to the benchmarks included in the regression.

The diversified time-series momentum strategy exhibits mainly significant beta coefficients on the momentum factor as proxied by UMD. The significance on momentum factor UMD is also confirmed with respect to the futures markets explored by Moskowitz et al. (2012) and Baltas and Kosowski (2012). This finding suggests that some variation in returns can be explained by cross-sectional momentum. None of the other factors included can explain the time-series momentum profitability, except for the commodity benchmark GSCI, which captures some of the time-series momentum profitability with regard to commodity indices. Nevertheless, the significance observed in the alpha coefficients implies that GSCI and UMD capture only a part of the time-series momentum profitability, leaving an important part unexplained.

As a next step, the 12-1 time-series momentum strategy is evaluated with respect to equation 3.4, where the SMB, HML, and UMD factors of Fama and French are replaced with the "momentum everywhere" factors constructed by Asness et al. (2013).

[Insert Table 6 here]

Table 6 reports the risk-adjusted performance of the single diversified 12-1 time-series momentum strategy with the alternative control variables as specified previously. Once again, the strategy delivers significant alpha coefficients and loads significantly on the momentum factor (MOM). However, an important part of the time-series momentum profitability seems to remain unexplained. The significance of the momentum coefficients UMD and MOM implies that there exists an important relationship between cross-sectional and time-series momentum. This is further investigated in the next section.

4.4. Time-Series Momentum vs. Cross-Sectional Momentum

The previous section showed a significant relationship between the single diversified 12-1 time-series momentum strategy and two momentum factors, UMD and MOM. Therefore, it is essential to investigate further the potential association between these two investment philosophies. For this purpose, the single 12-1 time-series momentum strategy is regressed to its respective 12-1 cross-sectional strategy with regard to the dataset under investigation:

$$\boldsymbol{TSMOM_{t,i}^{(12,1)} = \alpha + \beta CSMOM_{t,i}^{(12,1)} + \varepsilon_t} \quad \textbf{(3.5)}$$

where $CSMOM_{i,t}^{(12,1)}$ is the equally-weighted average return across instruments of the single diversified cross-sectional momentum strategy in month *t* for asset class *i*, with a look-back period of 12 months and a holding period of 1 month.

[Insert Table 7 here]

Table 7 reports the alpha and beta coefficients from the regression specified in equation (3.5). It may be noted that the alpha coefficients are significant (even at the 10% level), indicating the out-performance of the time-series momentum. It is also interesting to note that the time-series momentum strategy loads significantly onto the cross-sectional momentum strategy, implying that cross-sectional momentum can predict a part of the time-series momentum. The predictability of time-series momentum from cross-sectional momentum is obvious for all asset classes, as well as at the aggregate level. However, the significance of the intercept even at the 10% level indicates that time-series momentum profitability cannot be entirely captured by cross-sectional momentum. These findings are in line with those reported by Moskowitz et al. (2012). Nonetheless, the cross-asset relationship between time-series and cross-sectional momentum cannot be reported in the present dataset. Thus, there may not be significant cross-correlations contributing to the association between time-series and cross sectional momentum.

5. Time-Series Momentum and International Mutual Fund Performance

Following the evidence of significant time-series momentum profitability, this section aims to investigate the relation between mutual fund performance and time-series momentum. In particular, we examine the nature of investment strategies followed by mutual funds and whether these can be related to trend-following strategies such as time-series momentum.

Existing time-series momentum literature focuses primarily on hedge fund behavior, particularly that of managed futures funds and commodity trading advisors (CTAs), which have been shown to follow time-series momentum strategies (Baltas and Kosowski, 2012; Moskowitz et al., 2012). As far as mutual fund behavior is concerned, the existing literature focuses on mutual fund performance with respect to cross-sectional momentum by examining quarterly holdings of mutual funds (Grinblatt et al., 1995). The findings suggest that mutual fund managers tend to be momentum investors who buy past "winners," but do not systematically sell past "losers." In this study, a simpler approach is followed, seeking to investigate mutual fund performance with regard to time-series momentum strategies. More precisely, monthly mutual funds returns net of management expenses and fees are regressed on 12-1 time-series momentum returns. Moreover, given the more traditional and risk-averse nature of mutual funds, mutual fund returns are also regressed on the returns of a long-only time-series momentum strategy. The particular strategy used is one of long-only investments in instruments that have been performing well over the past 12 months. In cases where there is a "sell" signal, the long-only time-series momentum involves investment in the three-month Treasury bill, which provides the risk-free rate. Hence, mutual fund performance according to these two strategies can be examined by the following models:

$$\boldsymbol{MF_{y,t} = \alpha + \beta TSMOM_{i,t}^{(12,1)} + \varepsilon_t} \qquad \textbf{(3.6)}$$

$$\boldsymbol{MF_{y,t} = \alpha + \beta Long_{i,t}^{(12,1)} + \varepsilon_t} \qquad \textbf{(3.7)}$$

where $TSMOM_{i,t}^{(12,1)}$ is the return of the single diversified time-series momentum strategy described previously, $Long_{i,t}^{(12,1)}$ is the equally-weighted average return across instruments of the single long-only time-series strategy in month *t* for asset class *i,* with a look-back period of 12 months and a holding period of 1 month, and $MF_{y,t}$ is the equally average return across mutual funds of type *y* in month *t*. Type *y* may refer to commodity, international, and global mutual funds. Both the standard time-series momentum strategy and the long-only strategy involve a look-back period of 12 months and a holding period of 1 month.

To better evaluate mutual fund performance, mutual fund returns are regressed on a specification model that includes certain control variables, as follows:

$$\boldsymbol{MF_{y,t} = \alpha + \beta_1 TSMOM_{i,t}^{(12,1)} + \beta_2 MSCI_t + \beta_3 GSCI_t + \beta_4 CSMOM_{i,t}^{(12,1)} + \varepsilon_t} \quad \textbf{(3.8)}$$

$$\boldsymbol{MF_{y,t} = \alpha + \beta_1 Long_{i,t}^{(12,1)} + \beta_2 MSCI_t + \beta_3 GSCI_t + \beta_4 CSMOM_{i,t}^{(12,1)} + \varepsilon_t} \quad \textbf{(3.9)}$$

where the first regressors in both equations are the same as those in equations (3.6) and (3.7), $MSCI_t$ is the return of the MSCI World Index at time *t*, $GSCI_t$ is the return of the S&P GSCI Index in month *t*, and $CSMOM_{i,t}^{(12,1)}$ the return of the single diversified cross-sectional momentum strategy described previously.

[Insert Table 8 here]

Table 8 reports the alpha and beta coefficients of the models specified above. It can be observed that in the case of the aggregate time-series momentum strategy, international mutual fund exhibit a significant beta coefficient for both the time-series and the long-only momentum strategy, indicating that mutual fund managers use trend-following strategies. Even more interesting to note is the different responses of mutual fund performance with respect to these two strategies. Specifically, mutual fund returns seem to be associated to a larger extent with long-only trend-following. This is evident from the beta coefficients of the long-only strategy, which deliver highly significant *t*-statistics in all panels, while this cannot be said in the case of the original time-series momentum. Besides, the R^2 improves dramatically when mutual fund returns are regressed on the long-only strategy. This confirms the fact that mutual fund managers do not systematically sell "losers" (here instruments in downtrend), as documented in cross-sectional momentum literature.

In addition, mutual fund returns are regressed to a series of other control variables. The results show that time-series momentum is unable to entirely capture mutual fund performance when controlling for other variables. Indeed, the significant intercepts indicate that an important part of mutual fund performance remains unexplained. In unreported results, it is also found that mutual fund returns are highly associated with cross-sectional momentum returns, but this association becomes insignificant when time-series momentum and other factors are included. More interestingly, though, when mutual fund performance is regressed on the long-only strategy alongside other control variables, mutual fund profitability seems to be entirely explained. The intercepts become insignificant in all three cases. Thus it can be concluded that even if mutual funds with no sales restrictions are included in the dataset, the long-only trend-following strategy alone seems to be the driving force behind mutual fund performance.

6. Consistency and Robustness Checks

6.1. Sample periods

The previous section provided evidence on the existence of time-series momentum across equity and commodity markets for a 44-year period. The present section aims to assess whether the previous findings are robust with respect to different time periods. For this purpose, the original sample period is divided into two equal sub-periods of nearly 22 years each. The first sub-period spans from December 1969 to November 1991, and the second sub-period from December 1991 to December 2013.

[Insert Table 9 here]

As Table 9 shows, time-series momentum strategies remain profitable and deliver significant annualized mean returns in all asset classes and for both sub-periods examined. However, during the second sub-period time-series momentum returns are more than double those from the first sub-period. This may be due to the fact that the period from 1992 through 2013 can be characterized as involving the most important recent bull markets as well as two important recessions (the dot-com recession and the global financial crisis), during which time-series momentum realized its largest profits.

6.2. Extreme Market Conditions

In this section, the abnormal performance of the aggregate single diversified 12-1 time-series momentum strategy is evaluated with regard to the market portfolio as proxied by the MSCI World Index.

[Insert Figure 2 here]

Figure 2 shows the growth of an investment of $100 in the aggregate 12-1 time-series momentum strategy and the MSCI World Index. The figure clearly highlights the superior performance of time-series momentum relative to the market throughout the whole sample period. More remarkably, though, the figure presents the different responses of time-series momentum and the market during recession periods defined by the NBER.[10] More precisely, during these recessions time-series momentum generated large gains, whereas the market incurred large losses. Similarly, time-series momentum experienced large gains during uptrends of the market.

An interesting case to notice is the global financial crisis that took place from December 2007 to June 2009. During this contraction, time-series momentum experienced losses in the first stage of the downturn, then delivered substantial profits for a long period, and finally incurred severe losses when the market started recovering. This finding highlights the mechanism and the intuition behind time-series momentum. During normal market trends, time-series momentum sets up long and short positions in instruments according to the signs of their cumulative return over a look-back period. For instance, if the market has been increasing (decreasing) over the look-back period, then time-series momentum will set up long (short) positions for most instruments. However, when the market experiences a reversal in either direction, then time-series momentum will initially incur large losses due to its

[10] National Bureau of Economic Research. Dates available at: http://www.nber.org/cycles/cyclesmain.html.

existing long or short positions. Subsequently, time-series momentum will benefit from this reversal and experience large profits since it will adjust its positions to the new market conditions. Therefore, time-series momentum strategies are highly profitable precisely when reversals continue for long horizons. The fact that time-series momentum experiences large gains during market downtrends highlights its use as a hedge for market losses. The following figure investigates further the relationship between time-series momentum and the market during recessions.

[Insert Figure 3 here]

Figure 3 presents the realized cumulative returns of the market and the 12-1 time-series momentum strategy during the stress periods throughout the sample period. The figure highlights the high profitability and out-performance of time-series momentum during these recessions and the losses experienced by the market. It is clear that time-series momentum substantially outperformed the MSCI index in five out of six stress periods, and delivered positive returns. Remarkably, the most striking differences can be observed during the global financial crisis, where the aggregate strategy delivered a surprising 22%, whereas the market portfolio experienced almost a 47% loss.

These results confirm those explored in the time-series momentum literature on futures markets and further support the hedging nature of trend-following strategies in different asset classes. This is intuitive given that financial crises occur gradually and thus time-series momentum strategies have enough time to adjust to long and short positions according to their cumulative returns over a certain look-back period. The hedging nature of the strategy under investigation is further explored in Figure 4.

[Insert Figure 4 here]

Figure 4 plots the monthly returns on the 12-1 time-series momentum against the returns on the MSCI World Index. The figure highlights the option-like behavior of time-series momentum. The "smile" indicates that the strategy performs best in extreme up-or-down market conditions. Fung and Hsieh (2001) demonstrate that trend-following strategies generate payoffs that are similar to an option straddle on the market, which is also the case in this figure. Indeed, the payoff reported in Figure 4 resembles that of an option straddle. This implies that returns on time-series momentum are not due to compensation for market crashes, which renders the explanation for time-series momentum profitability even more puzzling from a risk-adjusted perspective (Moskowitz et al., 2012).

6.3. The Future of Time-Series Momentum and the Role of Central Banks

In considering the performance of time-series momentum after the end of the global financial crisis in Figure 2, one may doubt its future and abnormal profitability. Although the cumulative return on the 12-1 time-series momentum strategy remains well above the market index, it seems that it entered a consolidation period for the first time during, and throughout, the sample period examined. In contrast, the market seems to have entered a new uptrend over the same period, and unexpectedly time-series momentum does not deliver substantial profits.

Interestingly, this observation coincides with periods of market intervention by central banks, which have adopted quantitative easing as a monetary policy to stimulate the global economy. However, this aggressive policy employed by central banks has also caused correlations across assets to be distorted, as a result of which trend-following patterns are threatened. In particular, in unreported results, this study finds that the long-term correlation across equity and commodity indices *pre*-crisis stood at 16%, whereas it has increased to nearly 60% *post*-crisis. This finding may suggest that over the last few years there have not been any distinct trend patterns across assets that time-series momentum can exploit so as to realize large gains. However, the existence of emerging markets seems to provide a good diversification benefit and protects time-series momentum profitability, since their correlation with commodity markets does not exhibit striking differences between the two periods. According to these results, it is reasonable to argue that time-series momentum has been threatened over recent years and that restoring correlations across assets to their normal *pre*-crisis levels may play a crucial role in recovering time-series momentum attractiveness.

7. Conclusion

We document a significant time-series momentum effect that is consistent and robust across global equity and commodity markets, examined over the last 44 years. Our results confirm those documented for futures markets, and a degree of market inefficiency in equity and commodity indices can be suspected.

By examining the return predictability across all instruments, this study depicts continuation patterns in monthly returns for the first 12 months and weaker reversals over longer horizons. These results are consistent with behavioral theories of initial under-reaction and delayed over-reaction by investors (Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999), and with the potential profitability of trend-following strategies.

Based on the existence of return predictability, we further construct time-series momentum strategies over various combinations of look-back and holding periods, and evaluate their profitability. We find that time-series momentum strategies exhibit strong and consistent performance across all asset classes for the first 12 months and subsequently decay or exhibit weaker reversals. These findings are consistent and robust across a number of subsamples, combinations of look-back and holding periods, and different sample periods.

Time-series momentum tends to outperform cross-sectional momentum, primarily during shorter holding periods. Moreover, it has little exposure to standard asset pricing factors, but seems to be highly related to all of the momentum factors examined. However, after further investigation of the relation between these two momentum phenomena, we find that cross-sectional momentum cannot entirely capture time-series momentum. Additionally, evidence has been found regarding the hedging nature of time-series momentum. In particular, time-series momentum delivers payoffs that are similar to those of an option straddle; it realizes its largest gains during extreme up-or-down market conditions. However, over the last few years correlations across assets have increased due to central bank interventions. As a consequence, there are fewer independent trend patterns from which time-series momentum can benefit. Finally, all types of mutual funds examined follow time-series momentum strategies to some extent, but they seem to have a preference for long-only trend-following strategies.

The evidence of the existence of time-series momentum in conventional asset classes directly challenges the random walk hypothesis and renders the theoretical background of market efficiency more puzzling. Besides, its high return premium in extreme market movements seems to contradict rational asset pricing explanations. Therefore, the present findings are more likely to support behavioral explanations such as theories of sentiment, which further challenge the notion of efficient financial markets. However, the existence of rational theories explaining time-series momentum should not be excluded, and may be fruitful subjects for future research.

The findings of this study have some important implications and offer new insights to the investment world. Specifically, they prove that trend-following strategies can be equally associated with asset classes and fund industries other than futures markets, managed futures funds, and CTAs. Given the increasing availability of international ETFs which are benchmarked to global equity and commodity indexes, our study serves as evidence that the investment opportunities that can be exploited are numerous and involve totally different asset classes. However, it would be worthwhile and challenging to examine whether time-series momentum can be an appropriate investment strategy for private investors considering transaction costs and the frequency of transactions that this strategy demands, as well as whether trend-following remains an attractive investment philosophy in light of intervention by central banks and the high levels of correlations across assets.

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Figure 1: *Time-Series Return Predictability*

The figure reports the *t*-statistics of the β coefficients for the pooled panel linear regression of monthly excess returns for all instruments combined on their own past monthly excess returns for lags h=1,2, ..., 60. The *t*-statistics are calculated using standard errors that are clustered by asset and time. The dashed lines represent significance level at 5%. The sample covers the period January 1970 through December 2013.

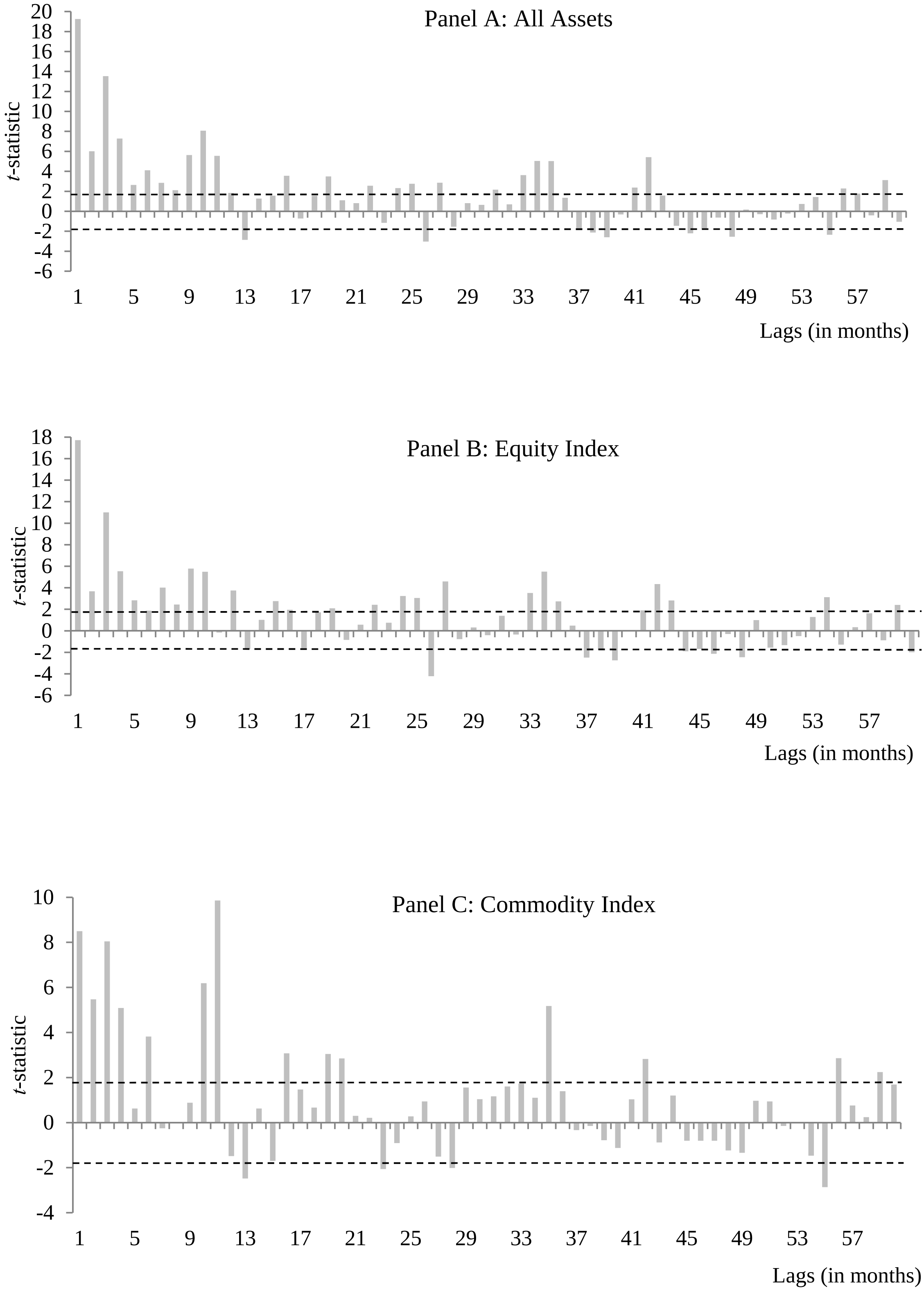

Figure 2: *Historical Performance of Time-Series Momentum*
The figure presents the growth of a $100 investment in the single diversified 12-1 time-series momentum strategy and the MSCI World Index. The sample covers the period February 1971 through December 2013.

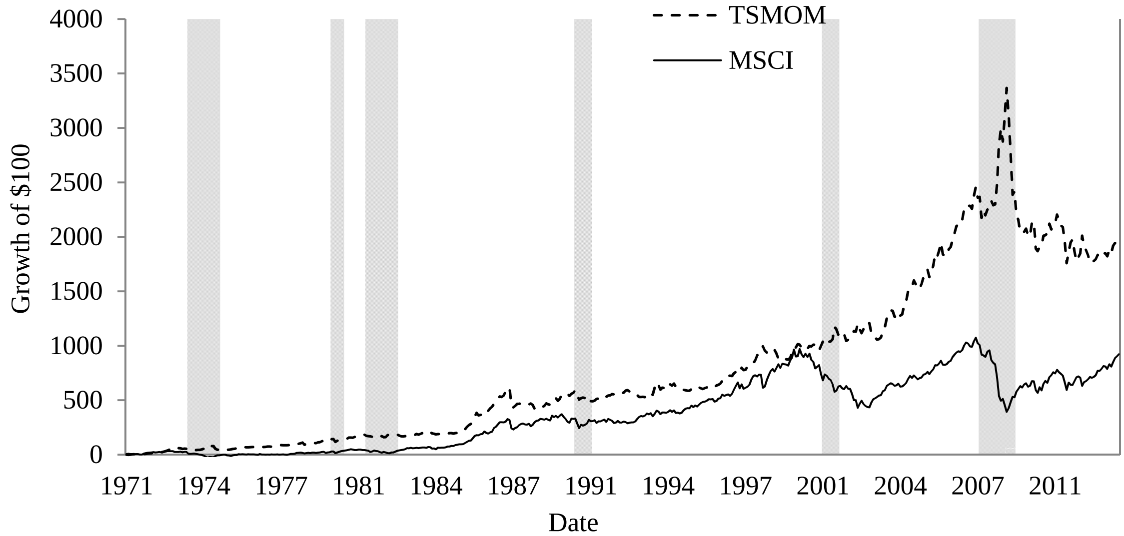

Figure 3: *Option-like Behavior of Time-Series Momentum*
The figure presents the cumulative returns of the single diversified 12-1 time-series momentum strategy and the MSCI World Index during recession periods defined by NBER.

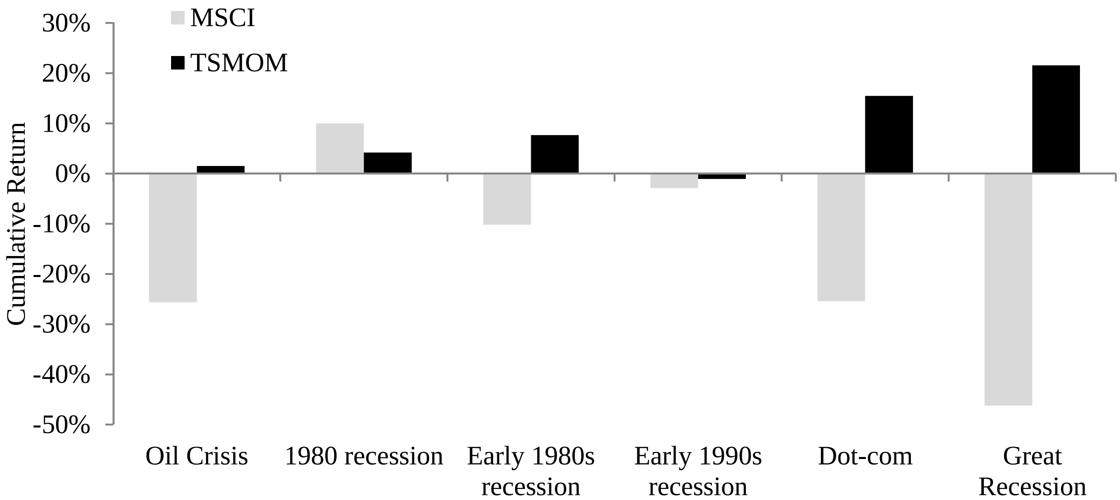

Figure 4: *Time-Series Momentum "Smile"*

The figure presents the scatterplot of monthly returns of the single diversified 12-1 time-series momentum against the returns of the MSCI World Index. The dashed lines represent the quadratic fit. The sample covers the period February1971 through December 2013.

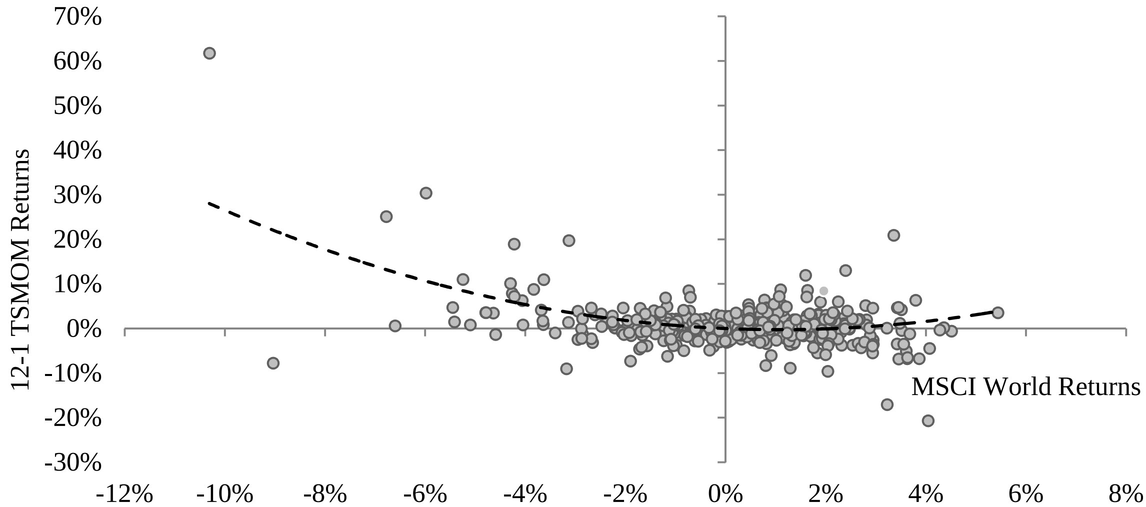

Table 1: *Descriptive Statistics*

The table reports summary statistics for equity and commodity indices. The annualized mean, annualized volatility (standard deviation), skewness and kurtosis are reported. The sample covers the period from December 1969 through December 2013.

	Data start date	Annualized mean	Annualized volatility	Skewness	Kurtosis
Equity Indices-Developed markets					
Australia	Dec-69	4.93%	87.39%	-1.50	9.80
Austria	Dec-69	5.79%	83.08%	-0.98	6.82
Belgium	Dec-69	6.24%	72.81%	-1.23	8.23
Canada	Dec-69	6.51%	69.58%	-0.90	3.55
Denmark	Dec-69	9.75%	68.32%	-0.48	2.34
Finland	Dec-81	11.30%	104.27%	-0.41	1.66
France	Dec-69	6.50%	79.36%	-0.48	1.46
Germany	Dec-69	7.06%	77.56%	-0.67	1.82
Hong Kong	Dec-69	10.37%	119.61%	-0.53	7.15
Ireland	Dec-87	2.06%	79.47%	-1.01	2.76
Israel	Dec-92	3.28%	83.33%	-0.47	0.88
Italy	Dec-69	2.48%	89.83%	-0.16	0.62
Japan	Dec-69	7.54%	73.34%	-0.02	0.67
Netherlands	Dec-69	7.38%	67.88%	-0.82	2.78
New Zealand	Dec-81	4.41%	89.92%	-0.91	5.02
Norway	Dec-69	7.80%	96.72%	-0.83	2.98
Portugal	Dec-87	-0.02%	81.47%	-0.42	1.79
Singapore	Dec-69	8.46%	99.04%	-0.52	5.93
Spain	Dec-69	3.72%	83.44%	-0.53	2.13
Sweden	Dec-69	10.00%	84.20%	-0.50	1.38
Switzerland	Dec-69	8.97%	63.47%	-0.40	1.33
United Kingdom	Dec-69	5.96%	74.61%	0.29	5.53
United States	Dec-69	6.53%	53.88%	-0.68	2.48
Equity Indices-Emerging markets					
Brazil	Dec-69	11.92%	180.37%	-1.39	10.90
Chile	Dec-69	11.21%	85.35%	-0.59	2.58
China	Dec-92	-2.19%	121.01%	-0.01	1.52
Colombia	Dec-92	11.14%	107.57%	-0.44	1.26
Czech Republic	Dec-94	6.87%	102.04%	-0.61	1.88
Egypt	Dec-94	10.06%	112.96%	0.00	1.80
Greece	Dec-69	0.65%	127.57%	0.04	3.02
Hungary	Dec-94	8.11%	135.94%	-1.07	4.37
India	Dec-92	6.69%	106.49%	-0.23	0.62
Indonesia	Dec-69	7.29%	159.55%	0.18	5.18
Malaysia	Dec-69	6.25%	96.90%	-0.29	4.70
Mexico	Dec-69	16.33%	108.98%	-0.99	3.51
Philippines	Dec-69	5.93%	107.00%	-0.18	1.98
Poland	Dec-92	10.40%	152.89%	0.49	5.77
Qatar	Jun-05	2.02%	104.76%	-0.62	2.28
South Africa	Dec-92	7.94%	95.81%	-0.92	2.55
Taiwan	Dec-69	4.09%	122.10%	-0.06	1.64
Thailand	Dec-69	4.81%	131.23%	-0.54	2.43
Turkey	Dec-69	5.84%	189.34%	-0.04	1.13
United Arab Emirates	May-05	-5.81%	132.50%	-0.40	1.95
Peru	Dec-92	11.43%	112.48%	-0.75	3.33
Korea	Dec-69	5.72%	125.06%	0.18	3.01
Commodity Indices					
Aluminum	Jan-91	-5.07%	66.71%	-0.05	0.58
Brent Crude Oil	Jan-99	14.94%	107.98%	-0.73	2.78
Cocoa	Jan-84	-7.54%	98.73%	0.26	0.79
Coffee	Jan-81	-5.89%	124.42%	0.49	1.86
Copper	Jan-77	4.97%	93.51%	-0.39	4.17
Corn	Dec-69	-4.71%	88.97%	0.56	3.36
Cotton	Jan-77	-2.17%	84.22%	0.06	1.16
Crude Oil	Dec-87	5.95%	112.99%	-0.14	1.72
Gas Oil	Jan-99	-0.05%	67.71%	0.09	3.24
Gold	Jan-78	2.78%	59.98%	-0.41	2.58
Heating Oil	Dec-82	4.42%	108.73%	-0.05	1.41
Lean Hogs	Jan-76	3.52%	94.25%	0.71	4.49
Live Cattle	Dec-69	-0.62%	115.87%	-0.36	6.15
Natural Gas	Jan-94	-29.39%	182.08%	-0.03	0.50
Nickel	Jan-93	-3.00%	85.82%	-0.27	0.62
Petroleum	Dec-82	13.89%	110.36%	-0.49	1.49
Platinum	Dec-83	-3.87%	135.53%	0.48	1.69
Soybeans	Dec-69	-4.42%	92.33%	0.24	2.10
Silver	Jan-73	-2.51%	89.43%	-0.54	3.55
Sugar	Jan-73	3.65%	120.60%	-0.17	0.45
Wheat	Dec-69	6.24%	106.27%	-0.17	1.97
Zinc	Jan-91	3.76%	77.86%	-0.56	4.36

Table 2: *Time-Series Momentum Strategies*

The table reports the annualized mean returns and the annualized Sharpe ratios for time-series momentum strategies across all asset classes with a look-back period of *J* months and a holding period of *K* months. The sample covers the period January 1970 through December 2013. Significance at the 1% and the 5% levels are denoted as *** and **, respectively.

Panel A: All assets														
K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualized mean return (%)							Annualized Sharpe ratio						
1	11.52***	4.68***	2.88***	2.64***	1.92***	0.96***	0.72***	0.73	0.67	0.67	0.71	0.6	0.45	0.44
3	11.16***	5.16***	3.84***	3.48***	2.40***	1.08**	0.96**	0.53	0.54	0.59	0.63	0.51	0.33	0.35
6	12.96***	6.60***	5.16***	3.72***	2.40***	1.32**	1.20**	0.58	0.58	0.61	0.52	0.41	0.3	0.31
9	15.36***	7.44***	4.80***	3.00***	2.16**	1.20	1.20	0.65	0.6	0.51	0.4	0.32	0.23	0.27
12	13.56***	5.76***	3.12**	2.04	1.44	0.96	0.84	0.56	0.45	0.34	0.26	0.2	0.17	0.19
24	3.60	0.84	0.12	0.12	0.24	0.48	0.48	0.15	0.06	0.01	0.01	0.03	0.08	0.07
36	3.72	1.08	0.72	0.72	0.60	0.36	0.24	0.17	0.09	0.07	0.09	0.08	0.05	0.04
Panel B: Equity Index														
K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualized mean return (%)							Annualized Sharpe ratio						
1	13.32***	5.28***	3.24***	2.88***	2.16***	1.20***	1.08***	0.69	0.58	0.59	0.59	0.53	0.43	0.43
3	11.28***	5.28***	4.32***	3.60***	2.64***	1.32**	1.20**	0.42	0.43	0.51	0.52	0.44	0.32	0.33
6	14.40***	7.80***	5.76***	4.08***	2.76**	1.56	1.32	0.50	0.53	0.53	0.45	0.35	0.28	0.28
9	17.40***	8.40***	5.40***	3.36**	2.28	1.56	1.56	0.57	0.53	0.44	0.34	0.27	0.23	0.26
12	14.52***	6.60***	3.60	2.16	1.44	1.32	1.20	0.47	0.40	0.30	0.21	0.16	0.18	0.19
24	3.96	1.08	0.48	0.60	0.84	1.08	0.84	0.13	0.07	0.04	0.05	0.08	0.13	0.10
36	5.04	1.80	1.56	1.56	1.44	0.96	0.48	0.18	0.12	0.13	0.15	0.15	0.10	0.05

Panel C: Commodity Index

K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualized mean return (%)							Annualized Sharpe ratio						
1	7.68***	3.60***	2.04***	2.16***	1.32***	0.36	0.24	0.48	0.52	0.44	0.59	0.41	0.19	0.18
3	10.80***	4.92***	3.00***	3.12***	1.80***	0.48	0.48	0.53	0.51	0.44	0.55	0.36	0.17	0.20
6	10.08***	4.44***	3.84***	2.88***	1.92**	0.72	0.72	0.47	0.40	0.47	0.42	0.32	0.17	0.21
9	11.16***	5.52***	3.48***	2.40**	1.80	0.36	0.48	0.50	0.46	0.39	0.33	0.28	0.08	0.12
12	11.40***	4.20**	2.28	1.92	1.20	0.12	0.24	0.50	0.34	0.25	0.24	0.18	0.03	0.06
24	2.76	0.12	-0.84	-0.96	-0.96	-0.72	-0.36	0.12	0.01	-0.08	-0.12	-0.13	-0.13	-0.09
36	1.08	-0.36	-1.08	-0.96	-1.08	-0.72	-0.12	0.05	-0.03	-0.11	-0.12	-0.14	-0.12	-0.01

Table 3: *Time-Series Momentum Strategies across Equity Markets*

The table reports the annualized mean returns and the annualized Sharpe ratios for time-series momentum strategies across equity markets with a look-back period of *J* months and a holding period of *K* months. The sample covers the period January 1970 through December 2013. Significance at the 1% and the 5% levels are denoted as *** and **, respectively.

Panel A: Equity Index														
K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualized mean return (%)							Annualized Sharpe ratio						
1	13.32***	5.28***	3.24***	2.88***	2.16***	1.20***	1.08***	0.69	0.58	0.59	0.59	0.53	0.43	0.43
3	11.28***	5.28***	4.32***	3.60***	2.64***	1.32**	1.20**	0.42	0.43	0.51	0.52	0.44	0.32	0.33
6	14.40***	7.80***	5.76***	4.08***	2.76**	1.56	1.32	0.50	0.53	0.53	0.45	0.35	0.28	0.28
9	17.40***	8.40***	5.40***	3.36**	2.28	1.56	1.56	0.57	0.53	0.44	0.34	0.27	0.23	0.26
12	14.52***	6.60***	3.60	2.16	1.44	1.32	1.20	0.47	0.40	0.30	0.21	0.16	0.18	0.19
24	3.96	1.08	0.48	0.60	0.84	1.08	0.84	0.13	0.07	0.04	0.05	0.08	0.13	0.10
36	5.04	1.80	1.56	1.56	1.44	0.96	0.48	0.18	0.12	0.13	0.15	0.15	0.10	0.05
Panel B: Developed Markets														
K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualized mean return (%)							Annualized Sharpe ratio						
1	13.92***	6.00***	3.84***	3.48***	2.76***	1.44***	1.20**	0.62	0.59	0.59	0.62	0.56	0.43	0.39
3	13.32***	6.60***	5.40***	4.80***	3.72***	1.80**	1.44**	0.44	0.47	0.54	0.57	0.49	0.36	0.32
6	18.00***	9.72***	7.68***	5.88***	4.44***	2.28**	1.68**	0.55	0.57	0.59	0.53	0.46	0.33	0.3
9	20.76***	10.68***	7.56***	5.40***	3.84**	2.04	1.80	0.59	0.57	0.52	0.44	0.37	0.26	0.27
12	19.08***	9.48***	6.12***	4.20**	3.00	1.80	1.44	0.53	0.49	0.42	0.34	0.28	0.21	0.2
24	11.88**	5.28	3.36	2.64	2.52	2.04	1.44	0.34	0.28	0.22	0.19	0.2	0.19	0.15
36	7.68	3.12	2.28	2.16	2.16	1.32	0.60	0.22	0.16	0.15	0.16	0.17	0.11	0.06

Panel C: Emerging Markets														
K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualized mean return (%)							Annualized Sharpe ratio						
1	21.48***	7.80***	4.56***	3.60***	2.64**	1.44	1.56**	0.79	0.59	0.56	0.51	0.44	0.37	0.45
3	15.48**	6.60	5.28**	4.08**	2.76	1.32	1.68	0.40	0.37	0.44	0.41	0.32	0.22	0.33
6	18.24**	9.60**	6.48**	3.84	1.56	1.44	1.68	0.44	0.45	0.42	0.29	0.14	0.18	0.26
9	23.88***	10.44**	5.40	2.16	1.20	1.56	2.04	0.53	0.45	0.31	0.15	0.09	0.18	0.26
12	16.92	5.88	1.80	-0.12	-0.24	1.32	1.56	0.37	0.25	0.10	0.00	-0.02	0.13	0.17
24	-7.80	-5.76	-4.20	-2.64	-1.56	0.36	0.36	-0.18	-0.24	-0.23	-0.17	-0.11	0.03	0.03
36	4.20	0.84	1.32	1.68	1.44	0.96	0.36	0.10	0.04	0.08	0.11	0.11	0.07	0.03

Table 4: *Cross-Sectional Momentum Strategies*

The table reports the annualized mean returns for cross-sectional momentum strategies for all asset classes with a look-back period of *J* months and a holding period of *K* months. The sample covers the period January 1970 through December 2013. Significance at the 1% and the 5% levels are denoted as *** and ** respectively.

Panel A: All Assets							
K	1	3	6	9	12	24	36
J	Annualized mean return (%)						
1	3.12	4.34**	4.64***	4.99***	3.85***	0.98	1.28
3	6.07	4.57	6.36***	8.88***	5.20***	1.60	2.06
6	9.42***	9.30***	11.63***	9.54***	4.91**	1.84	2.42
9	13.98***	15.42***	12.02***	8.23***	4.57	1.93	2.56
12	13.82***	10.87***	7.29**	5.10	3.01	2.11	0.00
24	7.09**	5.30	4.38	3.48	2.93	2.16	2.12
36	5.57	4.33	3.60	3.08	2.26	1.09	1.00
Panel B: Equity Index							
K	1	3	6	9	12	24	36
J	Annualized mean return (%)						
1	2.18	4.28**	5.07***	4.89***	3.26***	1.19	1.10
3	4.95	4.87	6.99***	8.17***	5.03***	1.57	1.24
6	10.27***	10.32***	11.63***	9.05***	5.36**	1.78	1.61
9	13.38***	14.10***	11.43***	8.13***	4.99**	2.15	1.53
12	12.99***	9.91***	7.59**	5.17	3.31	1.58	0.88
24	4.76	4.12	3.47	2.77	1.62	-0.21	-1.57
36	1.38	0.86	0.10	-0.64	-2.02	-4.58**	-5.88**
Panel C: Commodity Index							
K	1	3	6	9	12	24	36
J	Annualized mean return (%)						
1	6.60	9.28***	6.33***	4.84**	3.44**	-0.22	0.25
3	10.16**	7.35	3.14	6.66**	3.25	-0.74	0.18
6	10.19**	5.30	6.08	5.64	2.03	-2.01	-0.47
9	8.20	9.99**	7.17	4.94	2.09	-1.38	1.00
12	8.94	5.82	2.74	1.66	-0.16	-1.92	0.68
24	1.44	0.35	-1.48	-1.92	-3.11	-0.87	2.03
36	3.43	1.37	-0.01	0.28	-0.30	1.36	4.70

Table 5: *Performance of the Diversified 12-1 Time-Series Momentum Strategy-1*
The table presents the beta coefficients and their respective *t*-statistics from regressing the equally weighted average across instruments return of the single diversified 12-1 time-series momentum strategy on (i) the monthly MSCI World Index return (ii) the monthly S&P GSCI Index return (iii) the SMB, HML and UMD which denote the Fama-French factors representing size, value and momentum across U.S. stocks. The sample covers the period January 1970 through December 2013.

Panel A: All Assets							
	Intercept	MSCI	GSCI	SMB	HML	UMD	R^2
Coefficient	0.51%	-0.00	0.02	-0.05	-0.07	0.06	1.66%
(t-statistic)	(3.78)	(-0.12)	(0.89)	(-1.15)	(-1.31)	(2.07)	
Panel B: Equity Index							
	Intercept	MSCI	GSCI	SMB	HML	UMD	R^2
Coefficient	0.56%	0.01	-0.02	-0.06	-0.07	0.06	1.03%
(t-statistic)	(3.19)	(0.28)	(-0.73)	(-1.02)	(-1.17)	(1.51)	
Panel C: Commodity Index							
	Intercept	MSCI	GSCI	SMB	HML	UMD	R^2
Coefficient	0.44%	-0.02	0.15	-0.06	0.00	0.08	7.39%
(t-statistic)	(2.69)	(-0.64)	(5.34)	(-1.11)	(0.06)	(2.21)	

Table 6: *Performance of the Diversified 12-1 Time-Series Momentum Strategy-2*
The table presents the beta coefficients and their respective *t*-statistics from regressing the equally weighted average across instruments return of the single diversified 12-1 time-series momentum strategy on (i) the monthly MSCI World Index return (ii) the monthly S&P GSCI Index return (iii) the VAL and MOM which denote the "momentum everywhere" factors reported by Asness, Moskowitz and Pedersen (2013), and represent the value and momentum across markets and asset classes. The factors are adjusted to account only for equity and commodity indices. The sample covers the period January 1970 through December 2013.

Panel A: All Assets						
	Intercept	MSCI	GSCI	VAL	MOM	R^2
Coefficient	0.43%	0.03	0.01	-0.02	0.15	3.25%
(t-statistic)	(2.55)	(0.91)	(0.32)	(-0.30)	(2.15)	
Panel B: Equity Index						
	Intercept	MSCI	GSCI	VAL	MOM	R^2
Coefficient	0.41%	0.00	-0.03	0.04	0.19	2.40%
(t-statistic)	(2.03)	(0.07)	(-0.88)	(0.68)	(3.17)	
Panel C: Commodity Index						
	Intercept	MSCI	GSCI	VAL	MOM	R^2
Coefficient	0.46%	-0.04	0.16	0.03	0.06	6.15%
(t-statistic)	(2.72)	(-1.17)	(5.61)	(0.59)	(1.31)	

Table 7: *Time-Series Momentum vs. Cross-Sectional Momentum*

The table reports the alpha and beta coefficients from regressing the single diversified 12-1 time-series momentum strategy (TSMOM) by asset class on its respective single diversified 12-1 cross-sectional momentum strategy (CSMOM). The sample covers the period January 1970 through December 2013.

	Independent Variable				
	CSMOM ALL	CSMOM EQ	CSMOM COM	Intercept	R^2
Dependent Variable					
TSMOM ALL	0.30			0.18%	45.27%
	(20.60)			(1.88)	
		0.09	0.22	0.21%	31.80%
		(7.31)	(12.32)	(1.89)	
TSMOM EQ		0.31		0.21%	27.06%
		(13.79)		(1.64)	
		0.30	0.01	0.42%	28.74%
		(12.80)	(0.44)	(2.89)	
TSMOM COM			0.23	0.18%	48.47%
			(21.16)	(1.75)	
		0.01	-0.03	0.22%	50.89%
		(0.81)	(-1.78)	(2.29)	

Table 8: *Time-Series Momentum and Mutual Fund Performance*

The table reports the alpha and beta coefficients from regressing returns of mutual funds (international, global and commodity funds) on the single diversified 12-1 time-series momentum strategy (TSMOM), the 12-1 long-only time-series momentum strategy (Long) and a number of control variables MSCI, GSCI, CSMOM. The sample covers the period February 1991 through December 2013 for equity indices and the period April 1997 through December 2013 for commodity indices.

Panel A: All Assets											
All mutual fund types-TSMOM						All mutual fund types-Long					
Intercept	TSMOM	MSCI	GSCI	CSMOM	R^2	Intercept	Long	MSCI	GSCI	CSMOM	R^2
0.78%	0.18				1.18%	-0.97%	0.70				34.09%
(3.98)	(2.48)					(-5.14)	(16.29)				
0.30%	0.05	0.78	0.18	0.02	77.61%	0.01%	0.15	0.71	0.18	0.01	78.41%
(3.65)	(1.58)	(37.33)	(11.45)	(1.10)		(0.13)	(4.65)	(28.03)	(11.52)	(0.58)	
Panel B: Equity Index											
International and global mutual funds-TSMOM						International and global mutual funds-Long					
Intercept	TSMOM	MSCI	GSCI	CSMOM	R^2	Intercept	Long	MSCI	GSCI	CSMOM	R^2
0.90%	0.02				0.04%	-0.09%	0.73				35.43%
(4.43)	(0.44)					(-5.04)	(16.78)				
0.34%	0.03	0.98	0.04	0.01	88.98%	0.15%	0.09	0.93	0.04	-0.00	89.27%
(5.01)	(1.23)	(62.48)	(3.01)	(0.50)		(1.81)	(3.93)	(47.92)	(3.11)	(-0.05)	
Panel C: Commodity Index											
Commodity mutual funds-TSMOM						Commodity mutual funds-Long					
Intercept	TSMOM	MSCI	GSCI	CSMOM	R^2	Intercept	Long	MSCI	GSCI	CSMOM	R^2
0.33%	0.22				1.47%	-1.20%	1.08				40.46%
(0.85)	(1.72)					(-3.64)	(11.63)				
2.07%	0.02	-0.01	0.68	0.01	78.92%	0.33%	0.08	-0.05	0.78	-0.02	86.53%
(10.59)	(0.19)	(-0.18)	(24.89)	(0.27)		(1.94)	(1.98)	(-1.57)	(25.51)	(-0.82)	

Table 9: *Time-Series Momentum Strategies-Robustness Check 1-subsample 1*

The table reports the annualized mean returns and the annualized Sharpe ratios for time-series momentum strategies across all asset classes with a look-back period of *J* months and a holding period of *K* months. The sample covers the period January 1970 through October 1991. Significance at 1% and 5% level is denoted as *** and **, respectively.

Panel A: All assets														
K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualized mean return (%)							Annualized Sharpe ratio						
1	7.68***	3.36***	2.40***	2.16***	1.68***	0.84***	0.60**	1.05	0.95	0.94	1.01	0.83	0.57	0.54
3	8.52***	4.32***	3.60***	3.36***	2.40***	1.08**	0.84**	0.80	0.79	0.92	1.00	0.80	0.53	0.54
6	9.84***	5.52***	4.56***	3.60***	2.52***	1.20**	0.96**	0.78	0.85	0.96	0.87	0.70	0.45	0.50
9	12.12***	6.48***	4.68***	3.36***	2.40***	1.20	0.96**	0.94	0.95	0.89	0.74	0.57	0.40	0.46
12	12.12***	5.88***	3.84***	2.76***	1.92**	1.08	0.84	0.96	0.86	0.73	0.59	0.45	0.36	0.38
24	6.36**	3.36**	2.40**	2.04	1.80	1.20	0.72	0.51	0.48	0.45	0.44	0.41	0.35	0.26
36	6.00**	3.00**	2.16	1.80	1.44	0.84	0.48	0.51	0.45	0.42	0.40	0.36	0.24	0.16

Panel B: Equity Index														
K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualized mean return (%)							Annualized Sharpe ratio						
1	1.44	0.84	0.24	0.36**	0.24**	0.12	0.00	0.94	0.93	0.89	0.92	0.77	0.56	0.52
3	2.16	1.08**	0.12	0.60***	0.60***	0.12	0.12	0.67	0.71	0.77	0.84	0.67	0.47	0.47
6	2.76	0.84	0.72	1.20***	1.08***	0.48***	0.24**	0.67	0.71	0.77	0.69	0.56	0.37	0.43
9	2.04	1.56**	1.08**	1.32***	1.08***	0.36**	0.24**	0.79	0.79	0.73	0.61	0.45	0.36	0.44
12	6.24***	3.12***	2.04***	2.04***	1.44***	0.48**	0.36**	0.78	0.7	0.57	0.44	0.32	0.32	0.36
24	4.56***	1.92**	1.20	0.84	0.60	0.12	0.24	0.39	0.38	0.37	0.39	0.39	0.4	0.34
36	5.28***	2.04**	0.96	1.20**	0.84	0.48	0.24	0.45	0.41	0.42	0.42	0.41	0.34	0.25

Panel C: Commodity Index														
K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualized mean return (%)							Annualized Sharpe ratio						
1	5.76***	1.56	1.44	1.32**	0.96**	0.24	0.24	0.57	0.33	0.42	0.53	0.45	0.2	0.17
3	7.68**	3.24**	3.48***	3.00***	2.16***	0.84	0.60	0.53	0.45	0.66	0.71	0.57	0.29	0.28
6	8.76**	5.04***	4.32***	3.36***	2.40**	0.96	0.72	0.54	0.6	0.74	0.69	0.54	0.32	0.26
9	10.32***	5.52***	4.08***	3.00**	2.28**	0.60	0.36	0.64	0.67	0.67	0.56	0.47	0.18	0.13
12	11.04***	5.28***	3.60***	3.00**	2.16	0.60	0.24	0.72	0.64	0.57	0.52	0.41	0.16	0.09
24	6.24	2.88	1.92	1.32	0.72	-0.36	-0.72	0.39	0.34	0.29	0.22	0.13	-0.07	-0.2
36	3.96	1.80	0.72	0.24	-0.24	-0.84	-0.72	0.23	0.19	0.1	0.03	-0.04	-0.21	-0.21

Table 9 (continued): *Time-Series Momentum Strategies-Robustness Check 2-subsample 2*

The table reports the annualized mean returns and the annualized Sharpe ratios for time-series momentum strategies across all asset classes with a look-back period of *J* months and a holding period of *K* months. The sample covers the period November 1991 through December 2013. Significance at 1% and 5% level is denoted as *** and **, respectively.

Panel A: All assets														
K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualized mean return (%)							Annualized Sharpe ratio						
1	15.24***	6.12***	3.36***	3.00***	2.04**	0.96	0.96	0.72	0.66	0.61	0.63	0.52	0.38	0.42
3	14.04**	6.24**	4.20**	3.48**	2.28	0.96	1.08	0.50	0.50	0.49	0.50	0.39	0.23	0.29
6	16.68***	7.92**	5.76**	3.72	2.28	1.20	1.20	0.57	0.53	0.51	0.41	0.30	0.23	0.26
9	18.48***	8.28**	4.68	2.64	1.80	0.96	1.32	0.60	0.51	0.38	0.26	0.21	0.16	0.23
12	14.64**	5.52	2.40	1.20	0.84	0.60	0.84	0.46	0.33	0.19	0.12	0.09	0.09	0.14
24	-0.12	-2.16	-2.40	-2.04	-1.32	0.00	0.24	0.00	-0.12	-0.18	-0.17	-0.12	0.00	0.02
36	2.04	-0.48	-0.72	-0.24	-0.12	-0.24	-0.24	0.07	-0.03	-0.05	-0.02	-0.02	-0.02	-0.03

Panel B: Equity Index														
K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualized mean return (%)							Annualized Sharpe ratio						
1	17.88***	6.48**	3.72**	3.00**	2.28**	1.20	1.20	0.70	0.54	0.52	0.48	0.45	0.37	0.40
3	13.92	5.88	4.80**	3.72	2.64	1.20	1.32	0.39	0.37	0.44	0.41	0.35	0.24	0.28
6	18.84**	9.72**	6.84**	4.44	2.64	1.68	1.44	0.50	0.51	0.48	0.37	0.27	0.24	0.23
9	21.60**	9.72**	5.64	3.00	2.16	1.44	1.68	0.53	0.46	0.36	0.23	0.19	0.17	0.22
12	16.20	6.84	3.24	1.56	1.08	1.08	1.20	0.39	0.32	0.20	0.12	0.10	0.12	0.14
24	0.60	-1.68	-1.80	-1.56	-0.72	0.36	0.24	0.01	-0.07	-0.11	-0.10	-0.05	0.03	0.02
36	3.12	0.00	0.00	0.36	0.36	-0.36	-0.84	0.08	0.00	0.00	0.02	0.03	-0.03	-0.08

Panel C: Commodity Index														
K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualized mean return (%)							Annualized Sharpe ratio						
1	9.60**	5.64***	2.64**	2.88***	1.56	0.36	0.36	0.47	0.68	0.48	0.65	0.39	0.17	0.19
3	14.28***	6.84***	2.76	3.12**	1.44	0.24	0.48	0.58	0.59	0.33	0.46	0.24	0.06	0.17
6	12.12**	3.96	3.36	2.28	1.44	0.36	0.72	0.47	0.30	0.33	0.28	0.20	0.07	0.20
9	12.12**	5.52	2.76	1.68	1.20	0.00	0.60	0.44	0.37	0.24	0.19	0.15	0.01	0.14
12	11.28	2.88	0.72	0.60	0.12	-0.36	0.24	0.39	0.19	0.06	0.06	0.02	-0.06	0.07
24	-1.56	-3.24	-3.60	-3.12	-2.52	-0.84	0.12	-0.05	-0.20	-0.31	-0.31	-0.28	-0.13	0.03
36	-0.24	-1.56	-1.92	-1.44	-1.32	0.12	1.08	-0.01	-0.10	-0.17	-0.14	-0.14	0.01	0.17