Enhanced time-series momentum strategies in alternative asset classes: evidence from commodities and currencies in the global market.

Guido Majoni

Dissertation written under the supervision of Professor Pedro Monteiro E Silva Barroso

Dissertation submitted in partial fulfilment of requirements for the MSc in Finance, at the Universidade Católica Portuguesa, January 2023.

ABSTRACT

An investor can diversify risk by investing in a leveraged time-series momentum portfolio. The study evaluates and compares the performance of risk-adjusted time-series momentum strategies proposed in the literature. Focusing on international contracts of commodities and currencies, managing the sign of the position by accounting for partial moments rather than a market-timing or solely volatility-timing leverage offers the highest Sharpe ratio. Enhancing time-series momentum in both sign and volatility-timing yields positive excess returns net of transaction costs, and extends, ex-post, the efficient frontier with a significant diversification benefit. However, the net profitability of systematic time-series momentum strategies has been low since the COVID-19 pandemic.

Title of Dissertation: Enhanced time-series momentum strategies in alternative asset classes: evidence from commodities and currencies in the global market.

Author: Guido Majoni

Keywords: Time-Series Momentum, Anomalies, International Financial Markets, Transaction Costs of Momentum, Asset Pricing

SUMÁRIO

Um investidor pode diversificar investindo em estratégias de *momentum* em séries temporais. Este estudo avalia e compara o desempenho de várias estratégias de momentum em séries temporais propostas na literatura que usam retornos ajustados ao risco. Focando-me em contractos internacionais de matérias primas e moedas, acho que gerir o sinal da posição tendo em consideração os momentos parciais, em vez de tentar adivinhar a direcção do mercado ou simplesmente gerir a volatilidade, oferece o rácio de Sharpe mais alto. Melhorar a estratégia de investimento de momentum em séries temporais com gerindo o sinal e a volatilidade gera retornos em excesso da taxa de juro sem risco, e líquidos de custos de transação, positivos e melhora, ex post, a fronteira efficiente com ganhos de diversificação significativos. Porém, a rentabilidade líquida de estratégias de investimento em momentum de séries temporais tem sido fraca desde a pandemia do COVID-19.

Título da Dissertação: Estratégias melhoradas de momentum em séries temporais em classes de activos alternativos: matérias primas e moedas no mercado global.

Autor: Guido Majoni

Keywords: Momentum em séries temporais, Anomalias, Mercados Financeiros Internacionais, Custos de Transação do Momentum, Preços de Ativos

Table of Content

1. Introduction

Nowadays, investments based on past trends are widespread and profitable in global markets, with various combinations, despite numerous critiques and related research. Understanding the *momentum* in the *time-series* of an asset is, therefore, fundamental for several investment strategies. According to Bird, Gao and Yeung (2016), "*the information in the momentum signals is concentrated in the tails of the return distribution, it is not that surprising that momentum is best implemented using time-series momentum"*, helping to improve the strategies implemented by numerous hedge funds (Baltas and Kosowski, 2016).

The actual existence of time series momentum across global asset classes appears questionable. Huang, Li, Wang and Zou (2020) assess that Moskowitz, Ooi and Pedersen's (2012) evidence of the modeled time-series momentum is weak, especially with a large section of asset classes, performing as well as a strategy based on the historical mean. Therefore, time-series momentum is unlikely to be statistically significant across all the traditional asset classes with the prediction on the past 12 months.

The study is structured around the work of Hanauer & Windmueller (2023) and assesses the performance of different momentum techniques proposed in the literature. The study is also closely related to the research of Moskowitz et al. (2012), Daniel and Moskowitz (2016) and Liu, Lu and Wang (2021). The final goal is to evaluate managed time-series momentum strategies' performance in the past two decades from an investor perspective, accounting for both the great financial crisis of 2008 and the COVID-19 pandemic of 2020.

This study contributes to the literature in different directions. It expands the risk-parity strategy of Moskowitz et al. (2012) by enhancing both the leverage and the position applied in the strategy, separately. It challenges the limitation proposed by Daniel and Moskowitz (2016) in addressing a market volatility-timing adjusting for the implemented leverage in time-series momentum. It implements the Liu et al. (2021) adjustment for the prediction of the position to undertake in the strategy, using risk measures based on partial moments. The choice of comparisons follows Hanauer and Windmueller (2023), where they compare constant, dynamic and downside volatility scaling for cross-sectional momentum[1].

[1] Respectively, from Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016) and Wang and Yan (2021). The study implements specular strategies for the time-series momentum (i.e., respectively, Moskowitz et al. (2012), an adaptation of Daniel and Moskowitz (2016) and Liu et al. (2021).

The study first notes a performance of the Moskowitz et al. (2012) time-series momentum worse than a simple *buy-and-hold* strategy[2]. Enhanced time-series momentum strategies are superior in both risk and returns when compared to past literature and simpler strategies. When managing for partial moments, considering upside and downside risk in both commodities and currencies, time-series momentum generates a significant alpha of 7.96%, a significant excess return of 7.50% and expands, ex-post, the efficient frontier of standard portfolios and its Sharpe ratio[3]. The Sharpe ratio increases from 0.53 to 0.85 in a portfolio with the four-factor model of Fama and French[4]. The diversification benefit is clear. A market volatility-timing approach for time-series momentum shows a similar, but weaker, pattern. The strategy yields a significant excess return of 4.87% and a Sharpe ratio of 0.42, increasing to 0.76 in the same portfolio cited before. Moreover, the complement to Daniel and Moskowitz (2016) resigns in the rejected hypothesis of market volatility-timing forecast ability in time-series momentum, confirming their pattern.

The performance of the enhanced strategies is similar in subsamples. The results still hold when considering the global financial crisis and COVID-19 pandemic, but all the strategies seem not implementable after 2008 when accounting for transaction costs. Sharpe ratios and excess returns show a decline in value, e.g., from 0.70 to 0.42 and from 10.11% to 5.88% for Liu et al. (2021) partial moments time-series momentum, as well as an increase in tail risk. The pandemic impacts negatively the reward per unit of risk, challenging the exploitation of the market anomaly. Transaction costs differ in the full sample and subsamples. The profitability of the managed strategies is positive with the two crises aggregated, e.g., with a transaction costs upper limit of 0.63% for Liu et al. (2021) partial moments time-series momentum. This result does not hold for the Moskowitz et al. (2012) time-series momentum, revealing the strategy not profitable net of transaction costs. Splitting the sample and accounting for the crises separately, the results show a negative trend for profitability. E.g., Liu et al. (2021) strategy can sustain a transaction costs limit of 0.88% in the first subsample to zero in the second subsample. The adjusted strategy of Daniel and Moskowitz (2016) shows similar, but weaker results. No other strategy yields positive excess returns after accounting for transaction costs. The 2020 pandemic shows a net change in the results.

---

[2] A clear result is an excess return of 4.28% and a Sharpe ratio of 0.35 over Moskowitz et al. (2012) 2.74% and 0.17.
[3] The alpha refers to a spanning regression on the standard Fama and French four-factor model and several benchmarks, aggregated.
[4] Several other optimizations have the same result.

Debate is ongoing on the fact that strategies based on the exploitation of certain market anomalies might be fading away. Novy-Marx (2012) argues that momentum is like an echo and proposed an enhanced investment strategy called "*fundamental momentum*". He defines the traditional cross-sectional momentum as an echo rather than a continuation in returns, with no model predicting it. His research analyses currencies, commodities and international indices, suggesting a genuine echo in momentum in these asset classes. Momentum therefore might fade, with Goyal and Wahal (2015) supporting this discussion, but there is no international evidence. Georgopoulou and Wang (2016) complement the theory by investigating the impact of QE-periods[5] on both equities and commodities, suggesting that the market intervention by central banks is challenging the performance of portfolios built around time-series momentum.

The focus of the study on both the great financial crisis and the pandemic supports the literature on these hypotheses, especially on the impact of a strong QE. Again, the subsample tests result in a significative impact of the pandemic period on the managed strategies, lowering the excess returns with a negative profitability net of transaction costs.

These performances depend on the asset classes. The literature recognizes the presence of momentum in currencies and commodities (i.e., in Asness, Moskowitz and Pedersen, 2013). In the past two decades, commodities have become an interesting diversification asset in the eyes of investors: S&P GSCI performs greater returns than S&P 500 since 1969 (Erb and Harvey, 2006), with low and negative correlation with equity markets (Conover, Jensen, Johnson and Mercer, 2010) and inflationary hedge capabilities (Rosales, 2017). However, since a growing trading volume since 2000, their diversification benefit is decreasing (Goldber, 2015). ***Fig. 1*** shows a clear decrease in cumulative excess return after the great financial crisis of the S&P GSCI index over the MSCI World index.

[5] Quantitative Easing periods.

Fig. 1: Cumulative Performance of commodity and equity global indexes
The figure displays the cumulative performance of S&P GSCI index excess returns and MSCI world excess returns over a period from July 1990 to December 2021.

2. Literature Review

Jegadeesh and Titman (1993) first published the asset pricing anomaly *momentum* and it is still persistent in the extensive related academic literature[6]. The market inefficiency of buying winners and selling losers' abnormal returns is present nowadays in both cross-sectional and time-series patterns. In its cross-sectional nature, the position is defined on the relative performance, but in its time-series nature the position is defined on the absolute past performance. Asness et al. (2013) present cross-sectional evidence of the anomaly across asset classes, varying from equity, currencies, commodities and industries to international securities. Moskowitz et al. (2012) introduces the time-series momentum with a risk-parity approach, referencing what is known in previous periods as trend-following investing[7]. The research is significant across international equity, currency, commodity and fixed-income markets in a period from 1985 to 2009[8]. By

[6] Levy (1967) first publishes a research on this market anomaly, but still today it has less impact than the research of Jegadeesh and Titman (1993).
[7] The research on trend-following investing, e.g., moving averages or breakout strategies, spaced in different fields: Slow diffusion of news (Hong and Stein, 1999), behavioral biases (Barberis, Shleifer and Vishny, 1998), equilibrium over-reaction due to positive feedback strategies (De Long, Shleifer and Summers, 1990), overconfidence (Daniel Hirshleifer and Subrahmanyam, 1998), herding (Welch, Bikhchandani and Hirshleifer, 1992), disposition effect (Shefrin and Statman, 1985; Frazzini, 2006), risk factor exposure and growth (Berk, Green and Naik, 1999; Liu and Zhang, 2008), fund flows (Vayanos and Woolley, 2013).
[8] Additionally, Baku, Fortes, Hervé, Lezmi, Malongo, Roncalli and Xu (2019) further confirm the persistence of time-series momentum in currencies.

considering a risk-parity approach, i.e., volatility timing, it is possible to manage the risk of the portfolio with leverage[9].

The presence of time-series momentum across asset classes has been discussed extensively in the academic literature, along with its performance in the global economy and markets[10]. My study relates to the literature considering the major critiques of the paper published by Moskowitz et al. (2012). Kim, Tse and Wald (2016) analyze the relationship between time-series momentum and Moskowitz et al. (2012) volatility scaling approach, stating that scaled time-series momentum returns are driven by leverage, and the actual profitability of the strategy is no better than a *buy-and-hold* strategy, considering the 2008 global financial crisis[11]. The study extends the discussion of Kim et al. (2016) including both the COVID-19 crisis and different risk-adjusted strategies that rely on leverage, and it confirms their previous results. Moreover, Huang et al. (2020) research put a question mark on the time-series predictability pattern of Moskowitz et al. (2012)[12], suggesting a new pattern for predicting time-series returns. They discuss the doubtful profitability of a broad asset class's time-series momentum portfolio, as well as their predictability on a learning window of 12-months. The study extends their research by implementing a smaller set of asset classes, aiming for a smaller distortion of the portfolio's returns, but it keeps the past 12-months learning window of momentum.

Managing the risk of a strategy is as well vastly explored in the academic literature. My study, therefore, touches on different alternatives to enhance Moskowitz et al. (2012) strategy, and its tendency to suffer crashes. Georgopoulou and Wang (2016) support the better performance of time-series momentum in extreme markets, but momentum crashes do occur with deep and persistent drawdowns. Daniel and Moskowitz (2016) demonstrate the importance of managing and predicting momentum crashes for cross-sectional momentum. They develop a dynamic scaling approach considering both market's volatility and state indicators, better adjusting the strategy according to not only the instrument's returns but also their market trend. Their challenge is to evaluate if these characteristics hold a time series momentum pattern. My study extends their

---

[9] As pointed out by Kazemi (2012), a risk parity approach refers to the use of leverage for managing the risk of the portfolio within the asset allocation, by weighting the position in every security with related leverage. It is common in the derivatives portfolio management of financial institutions.
[10] Baltas and Kosowski (2013) study the persistency across asset classes, Georgopoulou and Wang (2016) the performance in both developed and emerging markets and Petterson (2014) the relations with volatility states.
[11] The analysis sample size is set from 1984 to 2013.
[12] i.e., the past 12-months returns. All their analyses are performed on the same sample.

research in evaluating if the same pattern applies to time-series momentum. Following Hanauer and Windmueller (2023), this dynamic scaling is a fundamental alternative to compare to related strategies. Liu et al. (2021) monitor the dynamics of both the upside and downside risk of time-series momentum losses to better understand the trade position. This methodology is developed around Gao, Leung and Satchell (2018, 2022). It analyzes cross-sectional momentum and documenting a better performance than the well-known methodologies of Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016). This approach is similar to the approach of Daniel and Moskowitz (2016) on the investigation of losses in different market states.

3. Data and Methodology

3.1 Data

3.1.1. Contracts returns

The data sample contains daily excess returns for 23 futures contracts and 9 cross-currency pairs forwards contracts from January 2000 through December 2021. All the data is extracted from Refinitiv Datastream. ***Appendix A*** provides a detailed description of each contract and its data source. The choice of futures and forwards is focused on a constrained database from Moskowitz et al. (2012)[13]. The data span is retrieved to consider only the trading extension of futures contracts to digitalized trading (i.e., higher frequency trading, from 2000).

Following Bessembinder (1992) and Roon, de Nijman and Veld (2000), the data is modeled as daily returns from daily settlement prices using the nearest-contract (until the first trading day of the delivery month), then rolled-over to the second nearest-contract within the delivery month[14]. A continuously compounded series of daily data is therefore created[15]. The daily returns of the series are subsequently converted in monthly data[16].

Table 1 presents summary statistics of the full sample. There is a notable dominance of positive mean excess returns across both contracts and asset classes, but it highlights the difference

[13] i.e., commodities and currencies.
[14] These returns reflect a strategy of closing the position of the nearest contract and opening the position of the second nearest contract at the end of the trading month before the delivery date. The spot prices do not reflect the delivery prices, but rolling the contract considers the implied delivery prices as a proxy of futures prices, so considering the spot price and the roll yield (Bessembinder, 1992).
[15] The series is directly extracted from Datastream for the futures contracts and computed for forward contracts. See **Appendix A** for further details.
[16] Log of returns is therefore implemented for all the analyses.

in volatility between asset classes, with commodities vastly more volatile than currencies. These results are coherent with Moskowitz et al. (2012) sample statistics, making the diversification in portfolios challenging.

Table 1: Summary Statistics of the sample

Summary statistics on forward and futures contracts. Returns are reported as excess returns. The table reports the annualized mean, annualized volatility, skewness, excess kurtosis, and Sharpe ratio of every contract over the period from January 2000 to December 2021. For a detailed description of the sample see ***Appendix A***.

Asset Class	Contract Info	Annualized Mean (%)	Annualized Volatility (%)	Skewness	Kurtosis	Sharpe Ratio
Currencies	CAD TO USD FWD	0.80	8.79	0.08	5.31	0.09
	EUR TO USD FWD	0.09	9.28	0.14	3.00	0.01
	JPY TO USD FWD	-2.17	9.60	0.29	4.28	-0.23
	NOK TO USD FWD	0.43	11.96	-0.15	5.26	0.04
	SEK TO USD FWD	-0.48	11.35	0.13	3.54	-0.04
	CHF TO USD FWD	1.11	10.20	0.86	26.71	0.11
	AUD TO USD FWD	2.36	12.26	-0.76	12.31	0.19
	NZD TO USD FWD	3.41	12.70	-0.39	5.22	0.27
	GBP TO USD FWD	-0.28	9.32	-0.49	10.50	-0.03
Commodities	CORN	4.55	26.76	-0.11	4.62	0.17
	SOYBEANS	4.60	22.90	-0.45	4.36	0.20
	SOYBEAN MEAL	4.39	25.46	0.34	15.33	0.17
	SOYBEAN OIL	5.58	31.23	0.04	2.28	0.18
	WHEAT COMPOSITE	4.82	28.84	0.27	2.48	0.17
	LEAN HOGS	1.95	31.23	-0.59	19.08	0.06
	LIVE CATTLE	3.09	16.79	-2.06	43.97	0.18
	COCOA	4.76	28.08	-0.19	2.56	0.17
	COFFEE 'C'	2.50	32.55	0.27	2.97	0.08
	COTTON #2	2.73	27.95	-0.29	4.25	0.10
	SUGAR #11	5.06	54.07	0.01	7.68	0.09
	BRENT CRUDE OIL	5.13	34.45	-0.60	9.34	0.15
	LIGHT CRUDE OIL	4.71	37.61	-0.58	11.95	0.13
	GAS OIL	4.82	32.74	-0.31	5.78	0.15
	NATURAL GAS	1.86	49.00	0.18	6.22	0.04
	ALUMINIUM	2.14	20.50	-0.20	2.65	0.10
	HI GRADE COPPER	7.24	26.00	-0.20	4.65	0.28
	NICKEL	3.96	34.73	-0.15	3.80	0.11
	ZINC	5.06	27.97	-0.16	3.10	0.18
	GOLD 100 OZ	8.04	17.45	-0.05	7.36	0.46
	PLATINUM	3.63	25.38	0.28	22.99	0.14
	SILVER 5000 OZ	6.38	30.82	-1.15	11.26	0.21
	PALLADIUM	6.37	34.17	-1.15	22.70	0.19

3.1.2. Asset pricing benchmarks

The performance of each time-series momentum strategy is relatively evaluated on standard asset pricing benchmarks developed in the literature. The definition of market index differs for asset class: Daniel and Moskowitz (2016) implement an equal-weighted average of the relative benchmarks. Currencies are associated with the aggregated excess returns of DXI Dollar Index and Lustig RX factor. Commodities are associated with the excess returns of S&P Goldman Sachs Commodity Index (GSCI). Further long-short benchmarks are included in the analyses, namely the currency High-minus-Low factor from Lustig et al. (2011) and the developed world MSCI market factor, SMB, HML and UMD from Ken French' Web site (further referred to as FF4). See ***Appendix A*** for more details on the variables' data source.

3.2 Managed time-series momentum factors

Following Moskowitz et al. (2012) literature on cross-sectional momentum conversion to a time-series approach, the first step is to underly a simple trend-following strategy proposed as ***Eq.1*** on the monthly frequency:

$$r_{i,t}^{TSM} = sign(r_{i,(t-13,t-1)}) \cdot r_{i,t} \tag{1}$$

Where each *i*-contract position (either long or short) is defined as the sign of the past 12-month cumulative returns, chosen at each time *t*[17]. Therefore, the strategy requires monthly rebalancing. Diversifying the individual strategies in an equal-weighted portfolio (further referred to as TSM), the returns at time *t* follow ***Eq.2***:

$$r_{t}^{TSM} = \frac{1}{i_{t-1}} \sum_{i=1}^{i_{t-1}} sign(r_{i,(t-13,t-1)}) \cdot r_{i,t} \tag{2}$$

Deepening the analysis in managing time-series momentum, the notable volatility differences between assets and asset classes of ***Table 1*** justify Moskowitz et al. (2012) approach to volatility scaling. The scale compares the contracts and creates better a diversified portfolio. As Barroso and Santa-Clara (2015) pointed out, this approach prevents the results from being dominated by high-volatility assets. Therefore, a volatility-timing forecast with individual realized volatilities is

[17] This means a learning period of 12 months and a holding period of 1 month.

implemented as a scaling factor. For each contract, ex-ante volatility is forecasted for each time *t* using an exponentially weighted model[18]. The annualized realized variance at time t is shown in ***Eq.3***:

$$\sigma_{t-1}^2 = 252 \sum_{i=0}^{\infty} (1-\delta) \cdot \delta^i \cdot (r_{t-2-i} - \bar{r}_{t-1})^2 \tag{3}$$

Where each variance is annualized by 252 trading days, the weights $(1-\delta) \cdot \delta^i$ add up to one each *i*-time and the δ value is chosen so that $\sum_{i=0}^{\infty}(1-\delta) \cdot \delta^i \cdot i = \delta/(1-\delta) = 60$ days. $\bar{r}_{t-1}$ is the exponentially weighted moving average of the returns computed similarly. The model follows Moskowitz et al. (2012) specifications, and it lacks the look-ahead bias in the volatility estimation[19]. More specifically, each time *t* the model would refer to the *t-1* forecasted volatility.

The unscaled strategy of ***Eq.1*** is scaled for an individual weight of size $40\%/\sigma_{i,t-1}$, where $\sigma_{i,t-1}$ is the forecast from ***Eq.3*** and the 40% is an annualized target volatility is an inconsequential choice standard in the literature for comparison reasons. Applying the weight to the individual contracts in the portfolio, the constant volatility strategy is computed as ***Eq.4***. As strongly supported in the literature, this model is referred to as the benchmark strategy for managed time-series momentum (further referred to as cTSM).

$$r_t^{cTSM} = \frac{1}{i_{t-1}} \sum_{i=1}^{i_{t-1}} sign(r_{i,(t-13,t-1)}) \cdot \frac{40\%}{\sigma_{i,t-1}} \cdot r_{i,t} \tag{4}$$

Daniel and Moskowitz (2016) enhance the constant scaling momentum of the cross-sectional momentum of Barroso and Santa-Clara (2015) with the forecasted strategy returns. In this sense, as discussed in Hanauer and Windmueller (2023), the scaling weight refers to the expected Sharpe ratio of the strategy, rather than its risk. Following ***Eq.5***, the weight for each contract, at time *t*, is computed as:

$$w_{t-1}^{dTSM} = \left(\frac{1}{2\lambda}\right) \cdot \frac{\hat{\mu}_{t-1}}{\hat{\sigma}_{t-1}^2} \tag{5}$$

[18] Similar to a univariate GARCH model (see Moskowitz et al., 2012).
[19] Both by the model-specific characteristics and the lagged t-1 reference for time t.

Where λ is a time-invariant scalar that matches the volatility of the dynamic strategy to the volatility of the market[20]. $\hat{\mu}_{t-1} \equiv \mathbb{E}_{t-1}[r_t^{TSM}]$ $(\hat{\sigma}_{t-1}^2 \equiv \mathbb{E}_{t-1}[(r_{TSM,t}^2 - \mu_{t-1})^2])$ is respectively the forecast of the conditional expected returns (variance) of the unscaled momentum (***Eq.1***) both in-sample and out-of-sample. The expected return of momentum is forecasted following the fitted values from ***Eq.6***:

$$\hat{\mu}_{t-1} \equiv \mathbb{E}_{t-1}[r_t^{TSM}] = \alpha_0 + \gamma_{int} \cdot I_{B,t-1} \cdot \hat{\sigma}_{m,t-1}^2 + \varepsilon_t \tag{6}$$

Where $I_{B,t-1}$ is a bear market indicator that equals 1 if the past 24-months market returns are negative (0 otherwise), and $\hat{\sigma}_{m,t-1}^2$ is the market variance of the past 60 days, before time *t*[21]. The in-sample approach suffers from look-ahead bias. More specifically, the in-sample estimations of the mean are performed over the full sample, and the volatility computations are explained in detail in ***Appendix B***. The inclusion in the analysis is due to comparison reasons, as stated by both Daniel and Moskowitz (2016) and Hanauer and Windmueller (2023). The out-of-sample forecasts of the mean are fitted with an expanding window methodology[22], and the variance is forecasted with the same methodology as **Eq.3**[23]. To be coherent with cTSM, the weights for each contract are annualized. The dynamic time-series momentum portfolio is the following (further referred to as dTSM):

$$r_t^{dTSM} = w_{t-1}^{dTSM} \cdot r_t^{TSM} \tag{7}$$

Where w_{t-1}^{dTSM} is the aggregated weight for every contract and r_t^{TSM} is the unscaled strategy from ***Eq.2***[24].

Following Liu et al. (2021), partial moments of the contracts' returns are calculated as a measure of the upside and downside risk of excess returns[25]. They argue that partial moments may be used to measure the degree of variability in the momentum of an asset over time, assessing its

---

[20] The market is referred to as the equal-weighted market benchmark of ***Section 3.1.2***.
[21] The choice of 60 days is to be coherent with ***Eq.3***.
[22] Starting from an initial window of 6 months (as in Daniel and Moskowitz, 2016).
[23] Again, this choice is for consistency purposes. This simple adaptation follows the same methodology of Daniel and Moskowitz (2016), with a realized variance forecast based on the individual contract (as in Moskowitz et al., 2012; shown by ***Eq.3***) rather than an aggregated factor.
[24] The computations are initially calculated by contract, then aggregated as an equal-weighted portfolio. For consistency with previous equations, the inverse approach is shown. Results do not differ.
[25] This approach is closely related to Daniel and Moskowitz (2016) methodology on cross-sectional data.

stability and confirming the direction of the trend. They use the methodology to identify potential changes in the momentum trend and to generate more accurate trading signals. Following Winkler, Roodman and Britney (1972), they compute a general approach, using the squared deviations of the excess returns over (below) a target return. In each day *t*, upper (lower) partial moments, i.e., UPM (LPM), are computed for respectively upside and downside risk. Liu et al. (2021) explain that it is necessary to consider weekly excess returns over the last trading week (i.e., 5 days) to capture time series momentum losses during reversals. The following ***Eq.8*** summarizes the variable characteristics:

$$UPM_{i,dt} = \sum_{j=0}^{n-1} r_{i,d_{t-j}}^2 I(r_{d_{t-j}} > 0) \quad (LPM_{i,dt} = \sum_{j=0}^{n-1} r_{i,d_{t-j}}^2 I(r_{d_{t-j}} < 0)) \tag{8}$$

Where I is the indicator function of a statement (i.e., positive or negative). The variables are then converted to a monthly frequency as $UPM_{i,t} = \sum_{j=1}^{21} UPM_{i,dt}$ ($LPM_{i,t} = \sum_{j=1}^{21} LPM_{i,dt}$). The consideration of upside (downside) risk is related to assessing long/short positions. The managed time-series portfolio is therefore built to consider the partial moments in the choice of the position on the baseline time-series momentum cTSM (further referred to as pTSM):

$$r_t^{pTSM} = \frac{1}{i_{t-1}} \cdot \sum_{i=1}^{i_{t-1}} sign_{i,t}^{pTSM} \cdot \frac{40\%}{\sigma_{i,t-1}} \cdot r_{i,t} \tag{9}$$

Where $sign_{i,t}^{pTSM}$ is the trade long/short sign of the strategy at time *t* for each contract *i*. The partial moments' variables UPM and LPM indicate the trend of the strategy, and their value is the variability. Therefore, a positive excess return of an asset with low variability, i.e., UPM with a low value, indicates a buy signal; a negative excess return of an asset with low variability, i.e., LPM with a low value, indicates a sell signal. Liu et al. (2021) evaluate the relationship between upper and lower partial moments by ranking their values in a joint distribution. See ***Appendix C*** for a detailed description of the methodology.

3.3 Methodology

The methodology follows closely the structure proposed by Hanauer and Windmueller (2023) on the performance assessment of the different managed time-series momentum strategies. The first step is to evaluate the strategies by mean returns (and related significance), higher order moments (volatility, skewness and excess kurtosis), maximum drawdown and risk-reward measures (Sharpe, Sortino, Calmar and Information ratios). The second step is to compare the strategies to several benchmarks and standard factors with pair-wise spanning tests. The third step is to perform an ex-post Sharpe ratio optimization on the same benchmarks and standard factors. ***Section 3.1.2*** reports these factors' construction. The final step is to test the managed strategies' profitability on the respective portfolio turnover for controlling the transaction costs impact.

To evaluate a significant overperformance of the strategies over market benchmarks and related factors, the strategies are treated as the test assets in spanning linear regression on asset pricing benchmarks. The null hypothesis tests if test asset excess returns are spanned, i.e., that the alpha equals zero. If the alpha is significant, the strategy outperforms the benchmarks and extends the efficient frontier. Therefore, the intercept quantifies the magnitude of the generated abnormal excess return.

In mean-variance efficient portfolio optimization, the economic significance of a test asset is quantified by comparing how much a factor portfolio could gain from its inclusion. The analysis follows Ball, Gerakos, Linnainmaa and Nikolaev (2016) ex-post Sharpe ratio maximization methodology, calculating the best combination that yields the highest ex-post Sharpe ratio on the same sets of benchmarks and standard factors for each managed strategy[26].

As in Barroso and Santa-Clara (2015), round-trip costs are calculated to measure the break-even level of transaction costs that would make the strategy insignificant. At a certain α-significant level:

$$\text{Round-trip costs}_{\alpha=5\%} = \left(1 - \frac{1.96}{t-stat_s}\right) \cdot \frac{\bar{\mu}_s}{\overline{TO}_s} \quad (10)$$

Where $\bar{\mu}_s$ is the mean of returns, $\overline{TO}_s$ is the average monthly turnover and $t - stat_s$ is the t-statistic for each strategy *s*[27]. The methodology is useful as a substitute for a direct quantification of transaction costs by defining an upper border for the potential costs' value. The significance level critical value defines the level of the borderline i.e., a higher significant level leads to a higher break-even point[28].

---

[26] A Monte Carlo simulation is implemented with N=10,000 simulations each test. It allows short positions.

[27] See ***Appendix D*** for an accurate description of the turnover computation.

[28] A critical value of 2.58 is chosen for the 1% level and 1.64 for the 10% level.

4. Empirical Results

4.1. Comparison of performances

This section analyses the performance of different managed time-series momentum strategies, along with baseline methodologies such as a *buy-and-hold* strategy (further referred to as BAH) and the trend-following strategy (TSM, ***Eq.2***). Annual returns, t-statistics, higher order moments, maximum drawdowns and risk-reward measures are tabulated in ***Table 2*** for the full sample period, from January 2000 to December 2021. Overall, different managing techniques can better the reward of the investment.

Table 2: Strategies' summary statistics

Performance of the strategies over the full sample period, from January 2000 to December 2021. BAH is the buy-and-hold strategy. TSM is the baseline time-series momentum strategy (unscaled). cTSM is the constant scaling strategy. The strategies labeled as dTSM are respectively the result In-Sample and Out-of-Sample. pTSM is the Partial Momentum strategy. All series are discussed previously in ***Section 3.2***. The table reports the annualized mean of excess returns and volatility for the monthly series of every strategy, with the corresponding mean t-statistic in parenthesis. The table also reports skewness, excess kurtosis, and maximum drawdown, defined as the maximum cumulative loss between a peak value and subsequent down value in the monthly series. Sharpe ratio, Sortino ratio, Calmar ratio and information ratio are properly annualized. The information ratio takes cTSM as the benchmark.

Strategy	Annualized Mean (%)	Annualized Volatility (%)	Skewness	Kurtosis	Max Drawdown (%)	Sharpe Ratio	Sortino Ratio	Calmar Ratio	Information Ratio
BAH	4.28 (1.59)	12.17	-0.84	3.35	-43.11	0.35	0.44	0.10	0.14
TSM	-0.09 (0.05)	8.77	-0.59	3.17	-43.37	-0.01	-0.01	0.00	-0.43
cTSM	2.74 (0.75)	16.58	-0.22	2.60	-48.86	0.17	0.24	0.06	-
dTSM_is	14.04 (5.48)	11.55	1.71	8.01	-11.77	1.22	2.72	1.19	0.86
dTSM	4.87 (1.91)	11.52	1.81	10.53	-22.25	0.42	0.73	0.22	0.25
pTSM	7.50 (2.41)	14.04	0.39	1.59	-37.46	0.53	0.94	0.20	0.50

It is firstly notable how better a traditional buy-and-hold strategy yields in comparison to the cTSM and TSM in both terms of annual returns and maximum drawdown, as well as when considering the risk-reward measures. The buy-and-hold strategy is yielding also a greater frequency of small gains and few large losses, but it is more subjected to *tail events*, making it, in a sense, riskier. cTSM performs poorly in the sample period, with an annual Sharpe ratio of 0.17 and a large maximum drawdown -48.86%. BAH yields an annual return 1.54% greater than cTSM, with a Sharpe ratio of 0.35. TSM presents lower volatility than both series, with negative annual returns of -0.09%.

Managing time-series momentum with different methodologies improves significantly the performance. Implementing a dynamic scaling, both *in-sample* and *out-of-sample*, as well as predicting the position with partial moments, increases the Sharpe ratio by more than two to three times the baseline Moskowitz et al. (2012) strategy cTSM. The dynamic results between *in-sample* and *out-of-sample* are consistent with Daniel and Moskowitz (2016) performances: evaluating the strategy in-sample is more precise over the full sample, but with a *look-ahead* bias, and the out-of-sample strategy is more precise on the real-time implementation. The Sharpe ratio *in-sample* is indeed better than the *out-of-sample* ratio, from 1.22 to 0.42, along with a halved maximum drawdown, from -22.25% to -11.77%, but yielding the same annual return. The downside of dTSM is the excess kurtosis gain in value for the *out-of-sample* strategy. For further comparisons, only the *out-of-sample* dTSM estimation is considered.

In relative terms, pTSM substantially outperforms the other strategies in both higher-order moments and risk-reward measures. For every unit of total risk, pTSM can yield a return of 0.53. But given the positive skewed nature of the portfolio, with a value of 0.39, the Sortino ratio is considered[29]. Moreover, partial moments momentum earns the most skill, in terms of opportunity, against Moskowitz et al. (2012) strategy[30]. The steepest decline from peak to trough observed, i.e., the maximal loss of the portfolio, is consistent with Liu et al. (2021) findings, and supported by the Calmar ratio, lowering the loss of the constant volatility scaling and bettering its risk-reward capability[31]. Numerically, pTSM outperforms the other strategies with a Sortino ratio of 0.94 and an Information ratio of 0.50. The maximum drawdown is at -37.46%, with a Calmar ratio of 0.20. Partial moments momentum shows significant returns at both a 10% and 5% level, with a distribution of returns close to normal. The crash risk of momentum is therefore minimal. Dynamic scaling demonstrates a similar significance of returns at a 10% level, but with notable higher-order

[29] As Rollinger and Hoffman (2013), in commodity trading advisor (CTA) trend-following investing, usually characterized by positively skewed data, using the Sortino ratio (i.e., scaling the return of the portfolio with the downside volatility), can achieve the strategy with less risk than the one suggested by the Sharpe ratio (opposite with negatively skewed data). Qualitatively, it is addressed as a *sharper* ratio.

[30] As in Barroso and Santa-Clara (2015), an Information ratio is computed for each strategy against a common benchmark strategy, i.e., constant volatility scaling. The ratio should not depend on volatility scaling, and each series is normalized by its standard deviation before the computation.

moments. Managing momentum with a dynamic scaling fitted on a market helps in managing risk and losses more efficiently, but it increases crash risk, presenting a maximum drawdown of -22.25%, a skewness of 1.81 and an excess kurtosis of 10.53.

To further understand the similarity of returns between the series, ***Table 3*** shows pairwise correlation coefficients including also the market benchmarks.

Table 3: Strategies' correlation matrix

The table reports the spearman correlation coefficients for the time-series averages of the strategies presented in ***Section 3.2*** and in ***Table 2***, with a pair of benchmarks. GSCI is the benchmark for commodities as the S&P GSCI Index, CURR is the benchmark for currencies as an equal-weighted variable of DXI-Dollar Index and RX (from Lustig et al., 2011). See ***Section 3.1.2*** for additional details. The analysis is performed over the full sample from January 2000 and December 2021.

	BAH	**TSM**	**cTSM**	**dTSM_is**	**dTSM**	**pTSM**	**GSCI**	**CURR**
BAH								
TSM	0.14							
cTSM	0.14	0.91						
dTSM_is	0.00	0.26	0.29					
dTSM	0.07	0.58	0.63	0.52				
pTSM	0.30	0.60	0.71	0.23	0.42			
GSCI	0.70	0.11	0.08	-0.01	0.03	0.16		
CURR	0.24	-0.01	-0.02	0.08	0.00	0.00	0.15	

As directed by Hanauer and Windmueller (2023), strong correlations can be traced back to similar scaling weights (i.e., for pTSM and cTSM, see ***Eq.4*** and ***Eq.9*** for computational details). TSM is highly correlated with the dTSM, pTSM and especially the cTSM (0.91). With the inclusion of the market benchmarks, the table shows almost no correlation with the managed strategies.

Fig. 2 shows the cumulative performance of the managed, the simple trend-following and the buy-and-hold strategies, over the full sample period. Compared to TSM, all strategies increase in returns, with pTSM as the highest. During the crash in 2008, pTSM shows an upturn, and dTSM stabilizes in returns until the end of the sample. All the other series, as supported by the literature, perform a crash. COVID-19 crises show a similar pattern, with pTSM quickly rebalancing into an uptrend after a downtrend in late 2019.

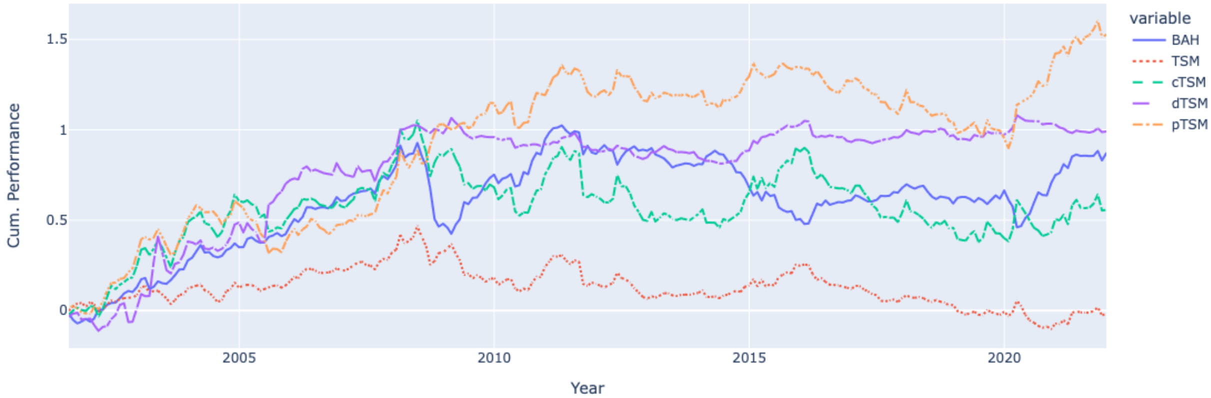

Fig. 2: Cumulative performance of the strategies
The figure displays the cumulative performance of the strategies explained above over the full sample period.

4.2. Spanning performance

A more formal test for assessing a factor's abnormal performance is a mean-variance spanning test to a standard asset-pricing model. Monthly time-series regressions of momentum strategies on benchmark and standard French and Fama factors, explained in ***Section 3.1.2***, are performed to understand and underline the importance of risk management in time-series momentum. The strategies are therefore referred to as test assets. ***Table 4*** evaluates the performance of the test assets on the benchmark CAPM-like models.

Table 4: CAPM-like spanning regression results
The table presents alphas and corresponding robust betas estimations (with White standard errors, and t-statistics in parenthesis) over the full sample period, from January 2000 to December 2021 (on a monthly frequency). The test variables are the time-series momentum strategies. See ***Section 3.2*** for a detailed description of the variables. Panel A presents the spanning test for the market excess return (as an equal-weighted portfolio of the GSCI Index and the currency markets). Panel B presents the spanning test for the MSCI world index excess returns, measured in USD, minus the risk-free rate (US T-bill 1M rate). All estimations are in percentage points based on annualized data (series data multiplied by 1200 before the estimation). The significant level is shown as a * for respectively 10%, 5% and 1%. For each test asset s, the regression equation is represented by: $s_{i,t} = \alpha_i + \beta_i \cdot Market_t + \varepsilon_{i,t}$.

Panel A: CAPM with benchmarks					
Dep. var.	BAH	TSM	cTSM	dTSM	pTSM
const	**5.00****	-0.07	2.68	**4.82***	**7.41****
	(2.28)	(0.03)	(0.73)	(1.88)	(2.38)
MKT	0.62***	0.02	-0.05	-0.05	-0.08
	(11.25)	(0.45)	(0.60)	(0.71)	(0.97)
R-squared	34.33	0.08	0.15	0.21	0.38

Table 4 (continued)

Panel B: CAPM with MSCI					
Dep. var.	BAH	TSM	cTSM	dTSM	pTSM
const	2.97	0.21	3.39	**5.18****	**8.33*****
	(1.12)	(0.11)	(0.92)	(2.01)	(2.67)
MKT	0.18***	-0.04	-0.09	-0.04	-0.1156**
	(3.76)	(1.17)	(1.33)	(0.89)	(2.02)
R-squared	5.52	0.56	0.73	0.33	1.66

Panel A shows significant spanning alphas over the market benchmark, at a 10% level, for dTSM and both at a 10% and 5% level for pTSM and BAH. These strategies can generate an annual alpha of 4.82%, 7.41% and 5% over the market, respectively. The significant market benchmark with the *buy-and-hold* strategy suggests a strong correlation between the two variables. ***Table 3*** confirms this result. BAH is strongly dependent on the GSCI index, which is important because the strategy is composed mostly of futures contracts on commodities. Panel B presents the spanned alphas over the equity market world benchmark, explaining significant alphas for both dTSM, at a 5% level, and pTSM, at a 1% level. Interestingly, the equity market yields a significant negative beta on pTSM, indicating a negative relationship[32].

Table 5 further inspect the evaluation by including additional benchmarks, the French and Fama four-factor model and a combination of the two. Panel A presents the spanning test for the selected benchmarks: GSCI is the benchmark for commodities as the GSCI S&P Index; CURR is the currency market excess return (as an equal-weighted portfolio of DXI Dollar Index and RX factor from Lustig et al. (2011)); HMLc is a High-minus-Low currency portfolio developed by Lustig et al. (2011). Panel B presents the spanning test for the Fama and French 4 factors model for the developed countries: MKT as the MSCI world index returns minus the risk-free rate (US T-bill 1M rate), SMB as size, HML as value, UMD as momentum (cross-sectional). Panel C presents the spanning test for Panel A and Panel B factors combined.

[32] This relation is consistent with Conover et al. (2010).

Table 5: Benchmarks spanning regression results

The table presents alphas and corresponding robust betas estimations (with White standard errors, and t-statistics in parenthesis) over the full sample period, from January 2000 to December 2021 (on a monthly frequency). The test variables are the time-series momentum strategies and the buy-and-hold strategy. See ***Section 3.2*** for a detailed description of their characteristics. Panel A presents the spanning test for the selected benchmarks. Panel B presents the spanning test for the Fama and French 4 factors model for the developed countries. Panel C presents the spanning test for Panel A and Panel B factors combined. All estimations are in percentage points based on annualized data (series data multiplied by 1200 before the estimation). The significant level is shown as a * for respectively 10%, 5% and 1%. The independent variables are not affected by multicollinearity in any panel. For each test asset s, the regression equation is represented by: $s_{i,t} = \alpha_i + \beta_i \cdot GSCI_t + \beta_i \cdot CURR_t + \beta_i \cdot HMLc_t + \varepsilon_{i,t}$ and $s_{i,t} = \alpha_i + \beta_i \cdot MKT_t + \beta_i \cdot SMB_t + \beta_i \cdot HML_t + \beta_i \cdot UMD_t + \varepsilon_{i,t}$.

Panel A: benchmarks					
Dep. var.	BAH	TSM	cTSM	dTSM	pTSM
const	**3.86****	0.03	2.83	**5.02***	**7.96****
	(2.22)	(0.02)	(0.76)	(1.95)	(2.54)
GSCI	0.32***	0.02	0.01	0.01	0.03
	(14.82)	(0.96)	(0.23)	(0.38)	(0.79)
CURR	0.60**	-0.10	-0.14	-0.37	-0.46
	(2.01)	(0.30)	(0.22)	(0.83)	(0.85)
HMLc	0.24***	-0.02	0.00	0.01	-0.09
	(4.41)	(0.30)	(0.02)	(0.16)	(0.88)
R-squared	59.54	0.41	0.04	0.34	0.89
Panel B: FF4 developed					
Dep. var.	BAH	TSM	cTSM	dTSM	pTSM
const	3.55	-1.39	0.79	4.13	**7.31****
	(1.38)	(0.75)	(0.22)	(1.61)	(2.33)
MKT	0.13***	0.00	-0.03	-0.01	-0.08
	(2.70)	(0.13)	(0.38)	(0.28)	(1.37)
SMB	0.41***	0.16*	0.23	0.08	-0.01
	(3.05)	(1.72)	(1.26)	(0.59)	(0.06)
HML	0.19*	0.07	0.05	-0.02	-0.04
	(1.85)	(0.90)	(0.34)	0.19	(0.33)
UMD	-0.09	0.27***	0.44***	0.18***	0.17**
	(1.56)	(6.34)	(5.31)	(2.93)	(2.38)
R-squared	13.37	15.08	11.34	3.93	4.25

Table 5 (continued)

Panel C: kitchen sink					
Dep. var.	BAH	TSM	cTSM	dTSM	pTSM
const	**4.06****	-1.41	0.58	4.19	**7.73****
	(2.32)	(0.76)	(0.16)	(1.61)	(2.45)
GSCI	0.32***	0.02	0.01	0.02	0.05
	(14.11)	(0.78)	(0.20)	(0.49)	(1.22)
CURR	0.50*	0.00	0.03	-0.31	-0.37
	(1.68)	(0.01)	(0.04)	(0.70)	(0.68)
HMLc	0.22***	0.04	0.10	0.06	-0.03
	(4.02)	(0.66)	(0.87)	(0.73)	(0.28)
MKT	0.02	-0.01	-0.03	-0.02	-0.09
	(0.57)	(0.36)	(0.50)	(0.41)	(1.53)
SMB	0.18**	0.15	0.21	0.07	-0.02
	(2.07)	(1.54)	(1.15)	(0.52)	0.14
HML	-0.08	0.05	0.02	-0.05	-0.07
	(1.09)	(0.59)	(0.14)	(0.42)	(0.56)
UMD	-0.07*	0.28***	0.45***	0.19***	0.16**
	(1.82)	(6.32)	(5.35)	(2.92)	(2.21)
R-squared	61.26	15.63	11.75	4.45	5.01

Panel A confirms the previous market benchmarks spanning alphas when controlling for the high-minus-low currency factor (HMLc). Panel B interestingly shows that pTSM' spanned alpha still generates a significant abnormal annual excess return of 7.31% at a 5% level on the FF4 model. The significance of cross-sectional momentum (UMD) is coherent with Asness et al. (2013) and Barroso and Santa-Clara's (2015) findings on the close relationship between currency momentum and stock momentum. The *kitchen sink* spanning regressions, tabulated in Panel C, consider jointly the benchmarks of Panel A and the factors of Panel B, confirming the persistency of pTSM's alpha as an effective factor able to extend the efficient frontier, with an annual abnormal excess return of 7.73%, significant at a 5% level.

4.3. Factor portfolios improvement

A further step in accounting for strategy-specific risk-to-return characteristics is to assess the economic significance in alphas that can extend the efficient frontier. The methodology, explained in ***Section 3.3***, consists in building tangency portfolios on the mean-variance efficient frontier of the benchmarks presented in ***Section 3.1.2***. The differences in these portfolios' Sharpe ratios measure the inclusion gain of the test asset. ***Table 6*** presents the tangency portfolios' weights and Sharpe ratios over the full sample, from January 2000 to December 2021.

Table 6: Maximum ex-post Sharpe ratios

This table presents the optimal weights for an optimal (maximized) ex-post Sharpe Ratio in different combinations of factors. Sharpe ratio values are annualized. The portfolios' weights are constrained between -1 and 1. Panel A combines the benchmarks discussed in ***Section 3.1.2***, including a High-minus-Low currency portfolio developed by Lustig et al. (2011) HMLc. Panel B combines the French-Fama 4 factor model for the developed countries: MKT as the MSCI world index excess returns minus the risk-free rate (US T-bill 1M rate), SMB as size, HML as value, UMD as momentum (cross-sectional). The results cover the full sample, described in ***Table 1***, from January 2000 to December 2021.

Panel A: Benchmarks	Optimal Weights							Sharpe
#	GSCI	CURR	HMLc		cTSM	dTSM	pTSM	Ratio
0	-4.97%	88.36%	16.61%					**0.35**
1	-4.66%	82.51%	15.36%		6.79%			0.39
2	-3.87%	72.13%	11.87%			19.87%		0.56
3	-4.07%	70.59%	13.27%				20.22%	0.67
Panel B: FF4 Developed								
#	MKT	SMB	HML	UMD				
0	36.91%	16.72%	5.23%	41.14%				**0.67**
1	36.61%	15.82%	4.99%	39.22%	3.36%			0.67
2	29.59%	11.15%	4.65%	27.86%		26.74%		0.76
3	29.00%	12.34%	4.97%	24.63%			29.06%	0.85

It is clear from the table the increasing benefit of including different, yield-growing, risk-managed factors. An investor trading the benchmarks would gain the same maximal annual Sharpe ratio as including Moskowitz et al. (2012) cTSM. When more advanced strategies are implemented, the Sharpe ratio improves from 0.39 to 0.56 and 0.67, respectively for cTSM, dTSM and pTSM. When considering an investor trading the FF4 factors, the same conclusions can be deduced for independently adding the test assets: the Sharpe ratio improves ex-post, respectively, at 0.67, 0.76 and 0.85 from a base portfolio of 0.67 for cTSM, dTSM and pTSM. These results are consistent with the spanned significant alphas for both dTSM and pTSM, and the apparent insignificance of cTSM. Moreover, the results are coherent with Gibbons, Ross and Shanken (1989), stating that the presence of spanned significant alphas can extend the efficient frontier in maximizing the Sharpe ratio when optimizing, ex-post, the asset allocation. Moreira and Muir (2017) confirm the positive alpha of volatility-managed strategies.

4.4. Transaction costs impact

All the strategies presented in ***Table 2*** are equal-weighted portfolios built as zero-cost long-short strategies. However, they ignore the impact of transaction costs. Moskowitz et al. (2012), as well as Liu et al. (2021), do not include the impact of transaction costs in the analyzes. Following up Barroso and Santa-Clara (2015), both monthly turnover and transaction costs are computed to stress the performance of each time-varying strategy, as tabulated in ***Table 7***.

Table 7: Turnover and break-even round-trip costs

The table presents the turnover and transaction costs measures for the series TSM, cTSM, dTSM and pTSM. Turnover is the average long-short portfolio turnover (monthly). Round-trip measures the break-even point as the upper border for transaction costs for the strategy at several significant levels (10%, 5%, 1%). The measure construction is discussed in ***Section 3.2***. The analysis is performed over the full sample, from January 2000 to December 2021.

	TSM	cTSM	dTSM	pTSM
Turnover (in %)	4.67	31.12	170.19	31.41
Round-trip costs at 10% sign. level (in %)	-	-	0.03	0.63
Round-trip costs at 5% sign. level (in %)	-	-	-	0.37
Round-trip costs at 1% sign. level (in %)	-	-	-	-

The turnover of each managed strategy is intuitively driven by the scale. In this sense, the risk-parity approaches increase the turnover to, 31.12%, 170.19% and 31.41% respectively for cTSM, dTSM and pTSM over the simple TSM. This result is solid on the volatility timing nature of the strategies. More specifically, the more the strategy is accurate in timing, the greater the associated weight. This result is especially notable in dTSM 170.19% average monthly turnover, in line with the findings of Daniel and Moskowitz (2016).

Describing the transaction costs levels that would render the strategies' excess returns statistically insignificant at several confidence levels, i.e., round-trip costs, positive profits are clear when transaction costs are below, 0.03% for dTSM, at a 10% confidence level, and 0.63% and 0.37% for pTSM and cTSM, at a, respectively, 10% and 5% confidence level. TSM is shown to be statistically non-implementable when including transaction costs, yielding a negative performance. Usually, these break-even points are small for futures contracts due to their liquidity and cheap trading costs on centralized exchanges. pTSM shows an interesting higher point, confirming the substantial profitability of the strategy. The results are coherent with the previous analyses, suggesting both dTSM and pTSM techniques of better risk management as statistically significant, as well as implementable, over the full sample period.

5. Robustness checks

5.1. Crises impact

Part of the goal of this study is to investigate the impact of the two last financial crises on the performance of managed time-series momentum strategies. The underlying question is to understand the benefits of risk management during turbulent times. To address an answer, the sample is split into two halves: the first subsample includes the 2008 financial crisis, spanning from January 2000 to December 2012; the second subsample includes the COVID-19 pandemic crisis, spanning from January 2013 to December 2021. Generally, the studies around time-series momentum are performed only considering the 2008 crisis. Moskowitz et al. (2012) describe the presence of time-series momentum previous to the big crash, and further studies (e.g., Kim et al., 2016) describe time-series momentum as no better than a buy-and-hold strategy with the inclusion of the 2008 crash. Liu et al. (2021) first consider the impact of the COVID-19 crisis on Chinese commodities, presenting positive results in supporting the pTSM approach. ***Table 8*** shows the performance of the strategies discussed above in the respective subsamples.

Table 8: Strategies summary statistics in the subsamples

Performance of the time-series momentum strategies in different subsamples. The first subsample is from January 2000 to December 2012. The second subsample is from January 2013 to December 2021. The table reports the annualized mean of excess returns and volatility for the monthly series of every strategy, with the corresponding t-statistic in parenthesis. The table also reports skewness, excess kurtosis, and maximum drawdown, defined as the maximum cumulative loss between a peak value and subsequent down value in the monthly series. Sharpe ratio, Sortino ratio, Calmar ratio and information ratio are properly annualized. The information ratio takes cTSM as the benchmark. pTSM strategies are computed differently for each subsample, see ***Appendix C*** for further details on the calculations.

Strategy	Annualized Mean (%)	Annualized Volatility (%)	Skewness	Kurtosis	Max Drawdown (%)	Sharpe Ratio	Sortino Ratio	Calmar Ratio	Information Ratio
Panel A: First Subsample (2000-2012)									
BAH	7.95 (2.00)	13.38	-1.13	3.95	-39.52	0.59	0.66	0.20	0.31
TSM	0.57 (0.19)	9.99	-0.87	2.94	-33.14	0.06	0.07	0.02	-0.50
cTSM	4.58 (0.86)	17.86	-0.66	3.04	-42.59	0.26	0.33	0.11	-
dTSM_is	13.99 (4.00)	11.76	2.79	19.91	-10.86	1.19	2.64	1.29	0.76
dTSM	6.27 (1.81)	11.66	1.51	6.46	-16.75	0.54	0.98	0.37	0.27
pTSM	10.11 (2.36)	14.41	0.07	1.15	-24.97	0.70	1.17	0.40	0.57

Table 8 (continued)

Panel B: Second Subsample (2013-2021)

BAH	0.66 (0.16)	11.01	-0.36	1.23	-27.22	0.06	0.09	0.02	0.01
TSM	-1.64 (0.59)	7.49	0.52	1.17	-30.12	-0.22	-0.38	-0.05	-0.64
cTSM	0.60 (0.10)	15.70	0.77	1.23	-40.74	0.04	0.08	0.01	-
dTSM_is	14.33 (3.17)	12.24	4.66	32.38	-6.36	1.17	3.57	2.25	0.79
dTSM	5.80 (1.30)	12.07	6.47	50.97	-11.77	0.48	1.72	0.49	0.40
pTSM	5.88 (1.13)	14.04	0.21	2.13	-33.38	0.42	0.64	0.18	0.36

In both subsamples, risk-managing time-series momentum with partial moments seems to reduce both skewness and maximum drawdown, yielding positive significant excess returns and improvements in the risk-reward measures. The drawdown is almost halved in Panel A, from -42.59% to -24.97%, and improved in Panel B, from -40.74% to -33.38%. More precisely, the risk is better rewarded, and excess returns are characterized by fewer small frequent losses and few large gains, with a positive skewness of 0.07 and 0.21. These results are consistent with Liu et al. (2021) findings. The result on the full sample period seems to hold in the first subsample, described in Panel A. pTSM is the highest performing strategy, with an annual excess return of 10.11%, a Sharpe ratio of 0.70 and an Information ratio of 0.57. As stated above, the cTSM performs worse than the BAH strategy, confirming the findings of Kim et al. (2016). Panel B shows a different scenario: after the global financial crisis and with the event of COVID-19 pandemic, BAH and cTSM perform closely, gaining almost no reward for the amount of risk undertaken (with Sharpe ratios almost null). dTSM and pTSM gain similar annual excess return, around 5.80%, but dTSM is *sharper* in rewarding risk, yielding both a Sortino ratio of 1.72 and a greater Sharpe ratio of 0.48. However, the strategy is extremely leptokurtic, being highly subjected to *tail risk*.

Combining the previous results in a mean-variance optimization setting, the tangency portfolios on the efficient frontiers show a similar pattern to the results in ***Section 4.3*** on the full sample. In both subsamples, the inclusion of a risk-managed strategy extends the efficient frontier, confirming Gibbons et al. (1989) and Moreira and Muir's (2017) research. The following ***Table 9*** summarizes the results.

Table 9: Maximum ex-post Sharpe ratio in the subsamples

This table presents the optimal weights for an optimal (maximized) ex-post Sharpe Ratio in different combinations of factors in different subsamples. The portfolios' weights are constrained between -1 and 1. Sharpe Ratio values are annualized. The first subsample, Panel A, is from January 2000 to December 2012. The second subsample, Panel B, is from January 2013 to December 2021.

Panel A: First Subsample (2000-2012)								
Benchmarks	Optimal Weights							Sharpe Ratio
#	GSCI	CURR	HMLc		cvol	dyn_OOS	pTSM	
0	-1.65%	90.56%	11.09%					**0.52**
1	-2.42%	86.24%	10.85%		5.33%			0.56
2	-2.37%	78.93%	7.55%			15.90%		0.76
3	-2.74%	78.85%	7.63%				16.26%	0.90
FF4 Developed								
#	MKT	SMB	HML	UMD				
0	11.08%	21.06%	55.06%	12.80%				**0.78**
1	9.44%	19.90%	56.25%	9.94%	4.48%			0.79
2	7.36%	13.41%	51.31%	7.42%		20.50%		0.90
3	6.67%	19.31%	47.02%	4.93%			22.07%	0.97
Panel B: Second Subsample (2013-2021)								
Benchmarks	Optimal Weights							Sharpe Ratio
#	GSCI	CURR	HMLc		cvol	dyn_OOS	pTSM	
0	-100.00%	100.00%	100.00%					**0.29**
1	-69.81%	100.00%	77.92%		-8.10%			0.29
2	-12.84%	-20.92%	45.80%			87.95%		0.52
3	-6.84%	27.12%	28.50%				51.22%	0.45
FF4 Developed								
#	MKT	SMB	HML	UMD				
0	100.00%	-52.14%	-39.30%	91.44%				**1.16**
1	100.00%	-51.11%	-41.25%	83.94%	8.42%			1.16
2	100.00%	-71.10%	-45.86%	66.64%		50.32%		1.25
3	65.23%	-17.43%	-20.69%	38.41%			34.48%	1.31

Measuring turnover and accounting for transaction costs is the final step in the study. As shown in ***Table 10***, Panel A confirms the results on the full sample, addressing both dTSM and pTSM as implementable in real-time, with a notably higher turnover of dTSM at 214.88%. Panel B shows a different scenario: besides the more than doubled turnover of dTSM, at 501.72%, none of the strategies yield a positive excess return when considering transaction costs at a 10%, 5% and 1% confidence level.

Table 10: Turnover and break-even round-trip costs in the subsamples
Turnover and transaction costs results in different subsamples. The first subsample is from January 2000 to December 2012. The second subsample is from January 2013 to December 2021.

	TSM	cTSM	dTSM	pTSM
Panel A: First Subsample (2000-2012)				
Turnover (in %)	4.97	28.39	214.88	28.88
Round-trip costs at 10% sign. level (in %)	-	-	0.02	0.88
Round-trip costs at 5% sign. level (in %)	-	-	-	0.50
Round-trip costs at 1% sign. level (in %)	-	-	-	-
Panel B: Second Subsample (2013-2021)				
Turnover (in %)	4.46	33.81	501.72	33.10
Round-trip costs at 10% sign. level (in %)	-	-	-	-
Round-trip costs at 5% sign. level (in %)	-	-	-	-
Round-trip costs at 1% sign. level (in %)	-	-	-	-

5.2. Conditional dependency of the methodologies

To further strengthen the study, the conditional statements presented in ***Section 3.2*** are tested with a series of regressions to understand the dependency of the strategies on market characteristics. First, a deep analysis is performed on Daniel and Moskowitz's (2016) dynamic scaling approach. The initial step is to test the null hypothesis of market-timing by the inclusion of the forecasted excess returns as a scaling factor (see ***Eq.5***). To understand this relation, the unscaled strategy is regressed on:

$$r_t^{TSM} = (\alpha_0 + \alpha_B \cdot I_{B,t-1}) + (\beta_0 + I_{B,t-1}(\beta_B + I_{U,t}\beta_{B,U}))r_{m,t} + \varepsilon_t \tag{11}$$

Where, at every month t, $I_{B,t-1}$is the ex-ante bear market indicator on the past 24-months, equaling one if the cumulative excess return is negative, zero otherwise; $I_{U,t}$is the contemporaneous monthly up-market indicator, equaling one if the market excess returns are positive, and zero otherwise; $r_{m,t}$ the market excess returns, i.e., the market factor described in ***Section 3.1.2***. The model is stressed over multiple combinations as a robustness check. ***Table 11*** confirms the significant impact, on average, of both the market excess returns and its interaction with the bear market indicator, on TSM at a 1% confidence level. These results are consistent with Daniel and Moskowitz's (2016) findings in the cross-sectional momentum of the aggregated currencies and commodities, pointing out that market-adjusted momentum is low following bear markets. The last row of the table tests the null hypothesis of the optionality of momentum excess returns during bear markets: the $I_{B,t-1} \cdot I_{U,t} \cdot r_{m,t}$ insignificant interaction demonstrates the adequate pricing of the contracts in the market, not rejecting the null hypothesis.

Table 11: First market-timing regressions

Estimation results (t-statistics) of four specifications of a monthly time-series regression over the full sample period. The dependent variable is the unscaled time-series momentum portfolio. The independent variables are a constant, the bear market indicator, the market excess return (as an equal-weighted portfolio of the GSCI Index and Dollar Index), and the contemporaneous up-market indicator. The coefficients $\hat{\alpha}_0$, $\hat{\alpha}_1$and $R^2$are in percentage points. The significant level is shown as a * for respectively 10%, 5% and 1%, with robust standard errors (Generalized Least Squares estimator). The independent variables are not affected by multicollinearity.

Coefficient	Variable	Estimated coefficients (t-statistics)			
		(1)	*(2)*	*(3)*	*(4)*
$\hat{\alpha}_0$	1	-0.01	-0.09	-0.09	-0.03
		(0.06)	(0.41)	(0.41)	(0.17)
$\hat{\alpha}_1$	$I_{B,t-1}$		0.23	0.2	
			(0.74)	(0.51)	
$\hat{\beta}_0$	$r_{m,t}$	0.02	0.21***	0.21***	0.21***
		(0.41)	(2.97)	(2.97)	(3.00)
$\hat{\beta}_B$	$I_{B,t-1} \cdot r_{m,t}$		-0.34***	-0.35***	-0.37***
			(3.63)	(3.01)	(3.46)
$\hat{\beta}_{B,U}$	$I_{B,t-1} \cdot I_{U,t} \cdot r_{m,t}$			0.02	0.08
				(0.10)	(0.52)
R^2		0.07	5.40	5.41	5.30

The further step is to evaluate if market variance and bear market state, both individually and jointly, impact the forecasts of excess returns of TSM. ***Table 12*** reports the results of the following regression:

$$r_t^{TSM} = \gamma_0 + \gamma_B \cdot I_{B,t-1} + \gamma_{\sigma_m^2} \cdot \hat{\sigma}_{m,t-1}^2 + \gamma_{int} \cdot I_{B,t-1} \cdot \hat{\sigma}_{m,t-1}^2 + \varepsilon_t \tag{12}$$

Where, for every month *t*, $I_{B,t-1}$is the bear market indicator and $\hat{\sigma}_{m,t-1}^2$ is the market variance of the past 60 days prior time *t*. In periods of market stress, with a bear market and high volatility, TSM excess returns are not, on average, affected. This result is, again, consistent with Daniel and Moskowitz's (2016) findings on the cross-sectional of the same aggregated asset classes (i.e., currencies and commodities). These results confirm that the strategy dTSM, as it is, is not suited for the considered contracts. However, it is interestingly able to outperform cTSM and BAH. They also confirm that TSM is low during bear markets, but it is not impacted by market volatility.

Table 12: Second market-timing regressions

Estimation results (t-statistics) of five specifications of a monthly time-series regression over the full sample period. The dependent variable is the unscaled time-series momentum portfolio. The independent variables are a constant, the bear market indicator, the market variance (from an equal-weighted portfolio of the GSCI Index and Dollar Index) and an interaction term. The coefficients $\hat{\alpha}_0$, $\hat{\alpha}_1$and $R^2$are in percentage points. The significant level is shown as a * for respectively 10%, 5% and 1%, with robust standard errors (Generalized Least Squares estimator). The independent variables are not affected by multicollinearity.

Coefficient	Variable	Regression				
		(1)	*(2)*	*(3)*	*(4)*	*(5)*
$\hat{\alpha}_0$	1	-0.15	0.17	0.02	0.03	0.27
		(0.65)	(0.77)	(0.11)	(0.12)	(0.68)
$\hat{\alpha}_1$	$I_{B,t-1}$	0.27			0.31	0.01
		(0.84)			(0.97)	(0.02)
$\hat{\gamma}_{\sigma_m^2}$	$\hat{\sigma}_{m,t-1}^2$		-35.57		-37.93	-89.48
			(1.25)		(1.33)	(1.28)
$\hat{\gamma}_{int}$	$I_{B,t-1} \cdot \hat{\sigma}_{m,t-1}^2$			-9.49		61.95
				(0.35)		(0.81)
R^2		0.30	0.62	0.05	1.00	1.26

Second, each contract's excess returns are assessed for market timing following ***Eq.14*** for each month. This approach, developed by Liu et al. (2021), is similar to Daniel and Moskowitz's (2016) previous evaluation.

$$r_{i,t} = \alpha_0 + [(\beta_U^+ I_{U,t-1} + \beta_{U,F}^+ I_{U,t-1} I_{F,t}) + (\beta_D^+ I_{D,t-1} + \beta_{D,R}^+ I_{D,t-1} I_{R,t})] UPM_{i,t-1} + [(\beta_U^- I_{U,t-1} + \beta_{U,F}^- I_{U,t-1} I_{F,t}) + (\beta_D^- I_{D,t-1} + \beta_{D,R}^- I_{D,t-1} I_{R,t})] LPM_{i,t-1} + \varepsilon_{i,t} \quad (13)$$

Where $UPM_{i,t-1}(LPM_{i,t-1})$ is the ex-ante upper (lower) partial moment on month *t-1*; $I_U(I_D)$ is the ex-ante upward (downward) momentum indicator in the cumulative excess returns of the past 12-month window, i.e., equals one if a long (short) signal is derived in the lookback window and zero otherwise; $I_F(I_R)$ is the contemporaneous monthly falling (rising) indicator equaling one if the contract excess return is positive (negative) at month *t*, and zero otherwise.

The results aim to understand which partial moment can capture future momentum reversal, via interactions of the indicators. ***Table 13*** presents the regression results. The model has a partial ability in predicting momentum reversals. Therefore, managing momentum considering large values of UPM and LPM is possible. More specifically, considering downward momentum, the estimated impact is stronger in the coming raising months of downward momentum than in the regular downward momentum for LPM. Looking at ***Table 13***, it is shown by $\left|\beta_D^{+,-} + \beta_{D,R}^{+,-}\right| < \left|\beta_{D,R}^{+,-}\right|$. This relation is inverted for UPM, with weak evidence. Considering upward momentum, the estimated impact is stronger in the coming falling months of upward momentum than in the regular upward momentum for UPM. Looking at ***Table 13***, it is shown by $\left|\beta_U^{+,-} + \beta_{U,F}^{+,-}\right| < \left|\beta_{U,F}^{+,-}\right|$. This relation is inverted for LPM. ***Appendix C*** shows the detailed implementation of these considerations.

Table 13: Partial moments market-timing regressions

Estimation results over the full sample, from January 2000 to December 2021. The dependent variable is the single contract monthly excess return. The model is specified in ***Section 3.2***. The significant level is shown as a * for respectively 10%, 5% and 1%, with robust standard errors (Generalized Least Squared estimations). R^2 is in percentage points.

Variable	1	$I_U \cdot UPM$	$I_U \cdot I_F \cdot UPM$	$I_D \cdot UPM$	$I_D \cdot I_R \cdot UPM$	$I_U \cdot LPM$	$I_U \cdot I_F \cdot LPM$	$I_D \cdot LPM$	$I_D \cdot I_R \cdot LPM$	
Coefficient	$\hat{c}_0$	$\hat{\beta}_U^+$	$\hat{\beta}_{U,F}^+$	$\hat{\beta}_D^+$	$\hat{\beta}_{D,R}^+$	$\hat{\beta}_U^-$	$\hat{\beta}_{U,F}^-$	$\hat{\beta}_D^-$	$\hat{\beta}_{D,R}^-$	R^2
Panel A: currency contracts:										
CAD TO USD FWD	-0.00	47.96***	-48.15***	2.53	31.21***	-8.91	-16.20	-10.10***	-10.77	63.68
EUR TO USD FWD	-0.00	50.61***	-45.67***	9.27*	16.53***	-21.28***	-7.49	-22.60***	26.96***	74.00
JPY TO USD FWD	0.00**	11.12***	4.23	11.90	12.93	3.44	-40.05***	-43.53***	20.87**	64.14
NOK TO USD FWD	-0.00**	45.13***	-40.35***	24.04***	5.37	-17.83***	-1.73	-13.93***	-12.30	66.52
SEK TO USD FWD	-0.00	42.41***	-35.31***	11.18**	10.37*	-19.95**	-1.17	-16.89***	8.16	68.14
CHF TO USD FWD	0.00	35.62***	-40.70***	15.78*	-12.83	-15.33*	5.02	-32.67***	54.34***	54.50
AUD TO USD FWD	-0.00*	33.23***	-23.03***	-0.80	30.44***	-4.50	-13.05	-3.96***	-13.07	65.34
NZD TO USD FWD	-0.00	32.57***	-23.25***	-0.92	23.41***	-11.86	-7.33	-7.20***	6.77	67.91
GBP TO USD FWD	-0.00***	50.90***	-32.31***	4.04	40.82***	-22.94*	-6.92	-12.39***	-0.66	69.16

Table 13 (continued)

Panel B: commodity contracts

CORN	0.00	10.38***	-10.69***	-2.59	10.58***	-2.86*	-4.28**	-9.29***	6.79**	66.16
SOYBEANS	-0.00	17.90***	-18.91***	-4.11	18.36***	-3.59	-4.28	-7.75***	3.28	69.56
SOYBEAN MEAL	-0.00	13.22***	-12.12***	0.92	4.77*	-5.71*	-1.53	-9.51***	21.03***	66.77
SOYBEAN OIL	-0.00	16.72***	-17.47***	3.61*	8.40***	-3.48**	-5.35***	-10.80***	8.85***	68.16
WHEAT COMPOSITE	-0.00	8.65***	-6.28***	0.81	10.18***	-3.67	-6.53*	-9.67***	6.45***	68.05
LEAN HOGS	0.00	7.95***	-12.34***	-0.08	7.13***	-5.26**	-0.80	-6.74***	4.32***	65.66
LIVE CATTLE	-0.01**	24.51***	-29.83***	-4.00	20.27***	-11.73**	7.27	-7.87***	2.88	63.56
COCOA	-0.01	11.66***	-8.20***	4.52	6.18	-5.64*	-1.52	-10.38***	9.65***	65.50
COFFEE 'C'	0.00	9.87***	-3.63*	7.86***	0.78	-3.27*	-7.65***	-13.00***	9.80***	70.36
COTTON #2	-0.00	11.13***	-5.69**	2.19	9.98***	0.51	-8.81**	-7.38***	3.87*	65.67
SUGAR #11	-0.00	6.18***	-1.50	3.15**	3.33**	-2.07	-5.07***	-4.77***	2.27	61.30
BRENT CRUDE OIL	-0.00	13.03***	-12.79***	2.24**	6.71***	-1.71	-4.06	-4.19***	-2.31**	68.70
LIGHT CRUDE OIL	-0.01**	13.51***	-11.43***	0.26	8.36***	-1.02	-5.03**	-3.40***	4.61***	73.28
GAS OIL	-0.01**	13.36***	-7.27**	-0.39	9.35***	-1.53	-3.89	-4.09***	5.18**	68.11
NATURAL GAS	0.00	5.42***	-6.07***	0.71	5.22**	-2.07	-3.39	-4.87***	4.35***	64.47
ALUMINIUM	-0.00	18.94***	-12.86***	0.39	11.57***	-17.56***	5.56	-8.10***	12.24**	66.98
HI GRADE COPPER	0.00	14.81***	-13.67***	-7.91***	16.74***	-11.66***	2.56	-3.67***	1.09	72.54
NICKEL	-0.00	10.35***	-9.28***	0.36	9.22***	-5.91**	-1.24	-5.20***	0.01	67.13
ZINC	0.01	10.26***	-11.86***	-0.19	11.77***	-11.87***	4.21	-7.61***	0.54	68.20
GOLD 100 OZ	0.01***	11.70***	-16.09***	-14.29*	15.39*	-9.52***	-2.89	-8.99***	21.30***	56.26
PLATINUM	-0.01**	11.81***	-1.37	7.13***	8.15***	1.05	-11.79***	-5.26***	6.91***	69.20
SILVER 5000 OZ	-0.01**	13.06***	-9.48***	-1.30	11.85***	0.45	-4.64***	-7.25***	6.15***	65.69
PALLADIUM	-0.02***	12.74***	-0.72	1.67	6.76***	-2.00	-5.17**	-3.02***	3.05	70.13

6. Conclusion

Managing upside and downside risk when considering the position in time-series momentum yields better performance. The reduction in tail risks, loss frequency, and the increase in Sharpe ratio is significant, better expanding, ex-post, the efficient frontier of a mean-variance investor. Other strategies underperform this methodology, under a risk-parity approach.

The results are confirmed for currencies and commodities, in different subsamples. However, the traditional predictability of time-series momentum weakens with the most recent COVID-19 financial shock. Transaction costs accountability shows the fading in excess returns of these strategies. Further research should exploit this study to further investigate time series momentum performance under different market-timing scenarios and predictability windows.

Appendix A. Data sources

A.1 Currencies

The selected currency forwards cover the following ten major global developed economies: Canada, Euro (spliced with Germany), Japan, Norway, Sweden, Switzerland, Australia, New Zealand, the United Kingdom and the United States. The daily excess returns of each contract *k*, denominated in USD, is computed following Lustig et al. (2011) ***Eq.14***:

$$rx_{k,t+1} = i_{k,t} - i_t - \Delta s_{k,t+1} \approx f_{k,t} - s_{k,t+1} \quad (14)$$

Where *k* refers to the foreign country, *f* and *s* are the *k*-country's forward (1 month) and spot exchange rates, i_k and *i* are the nominal interest rates for, respectively, the foreign country and the domestic country (i.e., United States). As in Asness et al. (2013), the MSCI spot rates and the middle short deposit interbank rates (as a proxy for Libor rates) are used. Following Arkam et al. (2008), the covered interest parity (CIP) is assumed to hold. To allow analysis to be independent of direct and indirect quotations, the natural logarithm of all exchange rates is used (Fama (1984)).

A.2 Commodities

The selected commodities cover 23 different contracts in the following major global exchanges. The data is collected as daily settlement prices denominated in USD. The contracts for Corn, Soybean, Soybean Meal, Soybean Oil, and Wheat are from the Chicago Board of Trade (CBOT); Lean Hogs, Live Cattle are from Chicago Mercantile Exchange (CME); Cocoa, Coffee *type C*, Cotton *number 2* are from Coffee, Sugar and Cocoa Exchange (CSCE); Brent Crude and Gas Oil are from Intercontinental Exchange (ICE); Light Crude, Natural Gas, Platinum, Palladium are from New York Mercantile Exchange (NYX); Copper, Gold, Silver are from New York Commodities Exchange (CMX); Aluminium, Nickel, Zinc are from London Metal Exchange (LME).

A3. Benchmarks

The selected benchmarks are modeled as logs of monthly excess returns. Lustig et al. (2011) RX factor is the average excess return on developed countries' currency portfolios and HML factor is the high minus low-interest rate portfolio on developed countries' currency. The developed French-Fama four-factor model refers namely to the MSCI world index excess return for the market, small minus big for size (SMB), high minus low for value (HML), and cross-sectional momentum (UMD). All data is extracted and available during the full sample period. All data is denominated in USD.

Appendix B. Dynamic in-sample model specifications

The dynamic strategy proposed in ***Section 3.2*** *in-sample* estimation requires conditional forecasting of volatility. Following Daniel and Moskowitz (2016), the first step is fitting a GJR-GARCH process to the daily TSM excess returns for each contract, summarized by **Eq.15**:

$$\hat{\sigma}_t^2 = \omega + \beta\sigma_{t-1}^2 + (\alpha + \gamma I(\varepsilon_{t-1} < 0))\varepsilon_{t-1}^2 \tag{15}$$

The GJR estimation is chosen to account for the leverage effect on the returns (Hansen and Lunde, 2005). The error terms derive from the regression $r_{i,t}^{TSM} = \mu + \varepsilon_t$, with $\varepsilon_t \sim N(0, \hat{\sigma}_t^2)$. The second step is regressing the future realized 21-day of the unscaled momentum excess returns on the GJR-GARCH estimation and the realized past 60-day realized volatility of the unscaled momentum excess returns. The realized variances are forecasted with an exponentially weighted model (as in ***Eq.3***). The following ***Eq.16*** fits the monthly data resulting from a conversion from the daily initial computations. The fitted estimations are annualized and used as input for the dynamic portfolio weight of Section ***3.2***.

$$\hat{\sigma}_t^{d21} = \hat{\alpha}_0 + \gamma_0 \cdot \hat{\sigma}_{t-1}^{GJR-GARCH} + \gamma_1 \cdot \hat{\sigma}_{t-1}^{d60} \tag{16}$$

Appendix C. Partial moments model specifications

C1. Choice of pTSM

The sign of ***Eq.9*** is the outcome of a non-linear relation $\mathcal{G}$, explained as:

$$sign_{i,t}^{pTSM} = \mathcal{G}\left(\sum_{i=1}^{i_{t-1}} sign(r_{i,(t-13,t-1)}), UPM_{i,t}, LPM_{i,t}\right) \tag{17}$$

Liu et al. (2021) generate expanding percentiles on the historical joint distribution of upper (lower) partial moments[33]. Every month *t* they rank the percentiles of every contract *i* based on the previous months' window and generate a sign referring to the reference points (UPM=0.60, LPM=0.80). ***Fig. C1*** shows the coordinate plane of UPM and LPM for the choice of position. *Condition 1* and *Condition 3* represent a high and low market volatility scenario with a more aligned distribution of partial moments, suggesting taking a long position in upward momentum stages and a short position in downward momentum stages, i.e., defining the sign as the TSM strategy of ***Eq.1*** [34]. As Liu et al. (2021) point out, the choice of the position in *Condition 2 and Condition 4* is not clear. In the case of upward momentum trend of *Condition 2*, the model predicts a slump in the price of the asset: with high downside risk (LPM) and low upside risk (UPM), the choice to buy or sell is ambiguous.

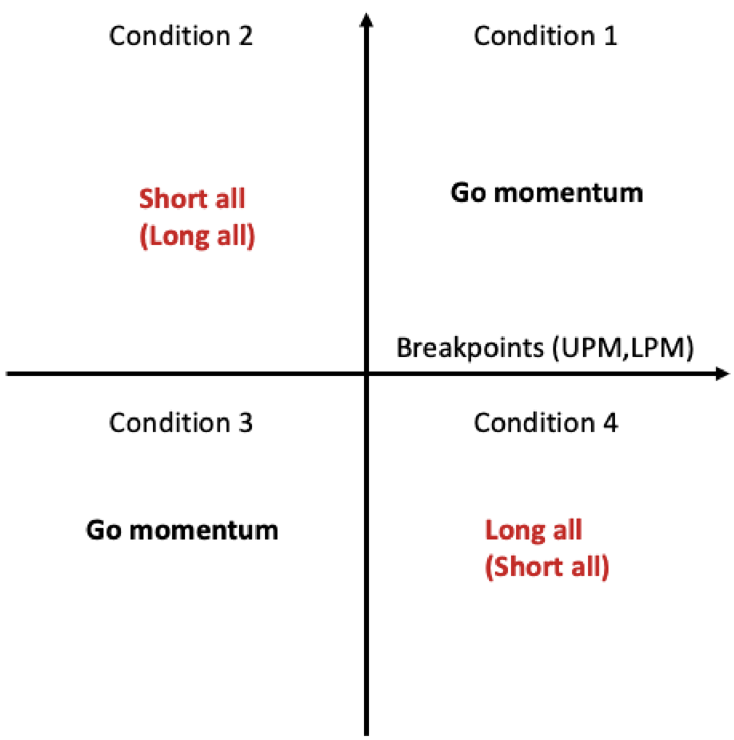

Fig. C1: Partial moments time-series momentum conditions
The figure presents the combinations of positions for the partial moments time-series momentum strategy, in relation to the chosen reference points.

[33] From an initial window size of 1.
[34] The choice of going momentum in region 1 is referenced to one of the options proposed by Gao et a. (2022). The baseline methodology of Liu et al. (2021) requires a position closed (equal to 0). In this sense, the objective is to always keep all the contracts in the portfolio.

Following ***Fig. C1***, the choice of the optimal sign combination depends on the recursive historical distribution of the partial moments with the reference points (0.60,0.80). **Table C1** shows the strategies methodologies and the associated Sharpe ratio. The optimal choice, for both the full sample and the first subsample, is to put a short (long) position in *Condition 2*, i.e., with a sign equal to -1 (*Condition 4*, i.e., with a sign equal to +1). For the second subsample, the optimal choice is inverted.

Table C1: Optimal choice of pTSM

pTSM strategy	Condition 1	Condition 2	Condition 3	Condition 4	Sharpe ratio
	Method	Method	Method	Method	
Panel A: Full sample					
S1	Go momentum	Short all	Go momentum	Long all	**0.53**
S2	Go momentum	Long all	Go momentum	Short all	0.02
Panel B: First Subsample (2000-2012)					
S1	Go momentum	Short all	Go momentum	Long all	**0.7**
S2	Go momentum	Long all	Go momentum	Short all	-0.56
Panel C: Second Subsample (2013-2021)					
S1	Go momentum	Short all	Go momentum	Long all	0.19
S2	Go momentum	Long all	Go momentum	Short all	**0.42**

C2. Choice of the reference points

The choice of the reference points for (60,80) is not inconsequential. Different combinations of values are tested in a sensitivity analysis reported in ***Table C2***. The pTSM strategy resembles the full sample optimal combination, with a short (long) position in *Condition 2* (*Condition 4*) of **Fig. C1**.

Table C2: Sensitivity analysis of the reference points

		LPM		
		0.60	0.70	0.80
UPM	0.60	0.37	0.49	0.53
UPM	0.70	0.34	0.47	0.51
UPM	0.80	0.28	0.41	0.46

Appendix D. Turnover computation

The turnover of a leg of the portfolio (long/short) is computed following Barroso and Santa-Clara (2015):

$$x_t = 0.5 \sum_i^{N_t} \left| \frac{w_{i,t}}{L_{i,t}} - \frac{\widetilde{w}_{i,t-1}}{L_{i,t-1}} \right| \quad (18)$$

$w_{i,t}$ is the weight of the instrument in the portfolio at time *t*, N_t is the total number of contracts in the leg of the portfolio at time *t*, $L_{i,t}$ is the weight used in the strategy at time *t* for each contract (e.g., for constant scaling $L_{i,t} = 40\%/\sigma_{i,t-1}$). In the case of an unweighted strategy, L_t is equal to 1. $\widetilde{w}_{i,t-1}$ is the weight of the contract in the current period right before its trading. The computation is shown in ***Eq.19***:

$$\widetilde{w}_{i,t-1} = \frac{w_{i,t-1}(1+r_{i,t})}{\sum_i^{N_t} w_{i,t-1}(1+r_{i,t})} \quad (19)$$

The weight of each contract in each portfolio is constant because of its equally weighting nature. The legs of the turnover are aggregated by sum. The turnover is calculated for every strategy proposed in ***Section 3.2***.

References

Akram, Q. F., D. Rime, and L. Sarno. 2008. Arbitrage in the Foreign Exchange Market: Turning on the Microscope. Journal of International Economics 76:237–53.

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. The Journal of Finance, 68(3), 929–985.

Baku, E., Fortes, R., Hervé, K., Lezmi, E., Malongo, H., and Roncalli, T., and Xu, J.(2019). Factor Investing in Currency Markets: Does it Make Sense? The Journal of Portfolio Management Quantitative Special Issue 2020, 46 (2) 141-155. https://doi.org/10.3905/jpm.2019.1.116

Ball, R., Gerakos, J., Linnainmaa, J. T., Nikolaev, V. V., 2016. Accruals, cash flows, and operating profitability in the cross section of stock returns. Journal of Financial Economics 121, 28–45.

Baltas, N., & Kosowski, R. (2013). Momentum strategies in futures markets and trend-following funds. In European financial data institute French finance association (EUROFIDAI-AFFI) paper, finance meeting, Paris December 2012.

Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics 49, 307–343.

Barroso, P., & Santa-Clara, P. (2015). Beyond the Carry Trade: Optimal Currency Portfolios. The Journal of Financial and Quantitative Analysis, 50(5), 1037–1056. http://www.jstor.org/stable/43862286

Barroso, P., Santa-Clara, P., 2015. Momentum has its moments. J. Financ. Econ. 116 (1), 111–120

Berk, J., Green, R.C., Naik, V., 1999. Optimal investment, growth options and security returns. Journal of Finance 54, 1153–1608.

Bessembinder, H., 1992. Systematic risk, hedging pressure, and risk premiums in futures markets. The Review of Financial Studies 5, 637–667.

Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy 100, 992–1026.

Bird, R., Gao, X., & Yeung, D. (2017). Time-series and cross-sectional momentum strategies under alternative implementation strategies. Australian Journal of Management, 42(2), 230–251. https://doi.org/10.1177/0312896215619965

Conover, C. M., Jensen, G. R., Johnson, R. R., & Mercer, J. M. (2010). Is now the time to add commodities to your portfolio?. The Journal of Investing, 19(3), 10-19.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. A theory of overconfidence, self-attribution, and security market under- and overreactions. Journal of Finance 53, 1839–1885.

Daniel, K., Moskowitz, T.J., 2016. Momentum crashes. J. Financ. Econ. 122 (122), 221–247. doi:10.1016/j.jfineco.2015.12.002.

De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Positive feedback investment strategies and destabilizing rational speculation. The Journal of Finance 45, 379–395.

Erb, C.B., and Harvey, C.R. (2006), The Strategic and Tactical Value of Commodity Futures, Financial Analysts Journal, 62(2), pp. 69-97.

Fama, E. F. (1984). Forward and spot exchange rates. Journal of Monetary Economics, 14:319-338.

Frazzini, A., 2006. The disposition effect and underreaction to news. Journal of Finance 61, 2017–2046.

Gao, Y., Leung, H., & Satchell, S. (2018). A critique of momentum strategies. Journal of Asset Management, 19(5), 341–350.

Gao, Y., Leung, H., Satchell, S. (2022). Partial moment momentum, Journal of Banking & Finance, Volume 135.

Georgopoulou, A., & Wang, J. (2016). The trend is your friend: Time-series momentum strategies across equity and commodity markets. Review of Finance, 21(4), 1557–1592.

Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A test of the efficiency of a given portfolio. Econometrica: Journal of the Econometric Society, 1121-1152.

Goldberg, S. (2015). Why commodities are bad investments. Kiplinger (pp. 1–2). Retrieved from: https://www.kiplinger.com/article/investing/t015-c007-s001-why-commodities-are-bad-investments.html

Goyal, A., & Wahal, S. (2015). Is Momentum an Echo? The Journal of Financial and Quantitative Analysis, 50(6), 1237–1267. http://www.jstor.org/stable/43862295

Hanauer, M., Windmüller, S., 2023. Enhanced momentum strategies. Journal of Banking & Finance, Volume 148, 106712, ISSN 0378-4266, doi:https://doi.org/10.1016/j.jbankfin.2022.106712.

Hansen, P.R. and Lunde, A. (2005), A forecast comparison of volatility models: does anything beat a GARCH(1,1)?. J. Appl. Econ., 20: 873-889. https://doi.org/10.1002/jae.800

Hong, H., Stein, J., 1999. A unified theory of underreaction, momentum trading and overreaction in asset markets. Journal of Finance 54, 2143–2184.

Huang, D., Li, J., Wang, L., & Zhou, G. (2020). Time series momentum: Is it there? Journal of Financial Economics, 135(3), 774–794. http://dx.doi.org/10.1016/j.jfineco.2019.08.004.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. Journal of Finance 48, 65–91.

Jusselin, P., Lezmi, E., Malongo, H., Masselin, C., Roncalli, T., & Dao, T.-L. (2017). Understanding the momentum risk premium: An in-depth journey through trend-following strategies. SSRN ELibrary, Available at: https://ssrn.com/abstract= 3042173.

Kazemi, H., 2012. An introduction to risk parity. Alternative investment. Anal.Rev.1, 20–31.

Kim, A. Y., Tse, Y., & Wald, J. K. (2016). Time series momentum and volatility scaling. Journal of Financial Markets, 30, 103–124.

Levy, R. A. (1967). Relative strength as a criterion for investment selection. *The Journal of finance*, *22*(4), 595-610.

Liu, L., Zhang, L., 2008. Momentum profits, factor pricing, and macroeconomic risk. Review of Financial Studies 21, 2417–2448.

Liu, Z., Lu, S., Wang, S., 2021. Asymmetry, tail risk and time series momentum, International Review of Financial Analysis, Volume 78, 101938, ISSN 1057-5219, doi:https://doi.org/10.1016/j.irfa.2021.101938.

Lustig, H., Roussanov, N., and Verdelhan, A. (2011). Common risk factors in currency markets. The Review of Financial Studies, 24:3731-3777.

Moreira, A. , Muir, T. (2017). Volatility-managed portfolios. J. Finance 72, 1611–1644.

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. Journal of Financial Economics, 104(2), 228–250.

Novy-Marx, R. "Is Momentum Really Momentum?" Journal of Financial Economics, 103 (2012), 429-453.

Pettersson, J. (2014). Time series momentum and volatility states. SSRN ELibrary, Available at: https://ssrn.com/abstract=2515685.

Rollinger, T. and Hoffman, S. (2013) Sortino Ratio: A Better Measure of Risk. Futures Magazine, February 2013, 40-42.

Roon, Frank A., Theo de Nijman, and Christian H. Veld, 2000, Hedging pressure effects in futures markets, Journal of Finance, 55, 1437–1456.

Rosales, E. B. (2017) Time-series and cross-sectional momentum and contrarian strategies within the commodity futures markets, Cogent Economics & Finance, 5:1, DOI: 10.1080/23322039.2017.1339772

Shefrin, H., Statman, M., 1985. The disposition to sell winners too early and ride losers too long: theory and evidence. Journal of Finance 40, 777–791.

Vayanos, D., Woolley, P., (2013), \An Institutional Theory of Momentum and Reversal," Review of Financial Studies, 26, 1087-1145.

Winkler, R. L., Roodman, G. M., & Britney, R. R. (1972). The determination of partial moments. Management Science, 19(3), 290–296.