Decomposing Time Series Momentum

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Highlights

- In this paper, we connect the two well-documented momentum effects in financial markets, time-series momentum (TSMOM, aka trend-following) and cross-sectional momentum (CSMOM), by introducing another momentum concept — asset-class momentum (ACMOM).
- Building an analytical decomposition framework, we show that both ACMOM and CSMOM are important components of TSMOM. Furthermore, the ACMOM has been the predominant driver behind the performance of TSMOM over the past half century. The findings explain why TSMOM is often found to be superior to CSMOM.
- We further show that the crisis alpha of TSMOM consistently came from the ACMOM of commodities and currencies, which is in contrast with the conventional wisdom that the crisis alpha of trend-following strategies mainly came from riding on the negative equity momentum.
- Examining the performance of Managed Futures/CTA indices, we find that the trend-following industry has been increasingly exposed to asset-class momentum, which likely diminishes the diversification benefits from multi-managers investing.

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Introduction

Time-series momentum (TSMOM) refers to the persistency of an asset's price behavior relative to its own time-series. That is, positive (negative) past price changes tend to be followed by positive (negative) future price changes. In a seminal work by Moskowitz, Ooi, and Pedersen (2012), the authors documented significant TSMOM effects across major asset classes and markets. Hurst, Ooi, and Pedersen (2013) further showed that TSMOM largely explained the performance of Managed Futures (MF) funds and Commodity Trading Advisors (CTA).

Cross-sectional momentum (CSMOM), on the other hand, refers to the persistency of an asset relative performance to its peers (typically within the same asset class). The CSMOM effects were first documented in the equity markets (see Jegadeesh and Titman 1993, and Rouwenhorst 1998 for evidence in the U.S. and global equity markets, respectively). Asness, Moskowitz, and Pedersen (2013) extended the analysis and found similar CSMOM effects across major asset classes and markets. In practice, CSMOM has been a key element in factor investing and risk management.

The linkage between TSMOM and CSMOM has been studied in the literature as well. Generally, research has shown that TSMOM is superior to CSMOM at similar horizons (Moskowitz, Ooi, and Pedersen 2012; Kolanovic and Wei 2015; Goyal and Jegadeesh 2017). For instance, using a regression approach, Moskowitz, Ooi, and Pedersen (2012) showed that TSMOM is related to but not fully captured by CSMOM across different asset classes (equities, bonds, commodities, and currencies). Specifically, when regressing the 12-month TSMOM returns on the 12-month CSMOM returns, the authors found significant beta of CSMOM as well as significant intercepts (alpha) across different markets. On the other hand, when the CSMOM returns were regressed on the TSMOM returns, the intercepts became insignificant and often negative, while the beta of TSMOM remained highly significant.

In this article, we attempt to bridge the gap between TSMOM and CSMOM by incorporating another momentum concept: the asset-class momentum (ACMOM). As a natural extension of TSMOM, ACMOM refers to the performance persistency of an asset class relative to its own history. While not studied as comprehensively as TSMOM and CSMOM, ACMOM has been well applied by practitioners in tactic asset allocation (TAA) strategies. For instance, Faber (2007) used a simple momentum signal (10-month moving average) to tactically allocate capital across five asset classes (U.S. stocks, foreign stocks, U.S. bonds, commodities, and real estates) and found superior risk-adjusted returns compared to buy-and-hold strategies.

We argue that both ACMOM and CSMOM are important components of TSMOM. Intuitively, the price of an asset may be influenced by either global factors that affect the whole asset class it belongs to, or idiosyncratic factors that only affect the specific asset. By the same token, an asset's time-series momentum could be driven by either the momentum of global factors (which manifests itself as ACMOM) or the momentum of asset-specific factors (which manifests itself as CSMOM). For instance, an upward momentum of oil price may reflect an upward momentum of the commodity asset class caused by global inflation expectation, or its relative upward momentum within the asset class due to the OPEC decision to cut supply.

We therefore propose an analytical framework to decompose TSMOM into ACMOM and CSMOM. Specifically, we create three diversified portfolios to capture the effects of TSMOM, ACMOM, and CSMOM, respectively. They are mathematically interconnected since the TSMOM of an asset is determined by the stronger effect of its ACMOM and CSMOM at any point in time. We show that over the past half century (1970–2019), while both ACMOM and CSMOM are important components of TSMOM, ACMOM has been a predominant driver behind the performance of TSMOM. Besides the ACMOM and CSMOM components, TSMOM also exhibits a significant alpha that presumably captures the diversification benefits from low correlations between ACMOM and CSMOM. The decomposition framework is further applied to analyzing the crisis alpha/risk premia properties of TSMOM, as well as explaining the MF/CTA industry performance.

Data

Our data consist of 60+ liquid futures/forwards contracts across major asset classes and the world: 23 commodity futures (CM), 13 equity index futures (EQ), 11 sovereign bond futures (BD), and 19 developed and emerging markets currency forwards (FX). Table 1 lists the instruments by asset class. Specifically, daily futures prices are collected from the Commodity Research Bureau (CRB) and Bloomberg, while daily FX spot prices and local short-term interest rates are collected from DataStream and Bloomberg. Daily futures returns are calculated assuming contracts are rolled to the next nearest contract on the first day of the expiration month. For financial futures (equity index and sovereign bond futures), we backfill the history using derived returns from cash instruments.[1] Daily FX forward returns are calculated as FX spot returns adjusted for carry. We construct a price index for each instrument by compounding daily returns, from which we can calculate returns and momentum signals of different horizons.

[1] Specifically, we backfill the equity index futures returns with the (gross dividends, excess cash) returns of the underlying indices. We backfill the U.S. Treasury futures returns with the derived returns from zero-coupon constant maturity yields of comparable duration. We find the real and derived returns for the equity indices and U.S. Treasury futures are almost identical in the overlapping periods (perfect monthly correlations and close to a 100% R-square).

Table 1. Data Coverage

Commodities (CM)			Equity Indices (EQ)	Sovereign Bonds (BD)	Currencies (FX)	
Soybean Oil	Brent Crude	Copper	Australian SPI 200	U.S. 2-year	AUD	BRL
Corn	WTI Crude	Aluminum	Canadian TSX 60	U.S. 5-year	CAD	CLP
Soybean Meal	Heating Oil	Nickel	German DAX	U.S. 10-year	CHF	CZK
Soybean	Gas Oil	Zinc	Spain IBEX 35	U.S. 30-year	EUR	HUF
Wheat	Natural Gas	Gold	France CAC 40	German 2-year	GBP	KRW
Cocoa	Gasoline	Silver	U.K. FTSE 100	German 5-year	JPY	MXN
Cotton			Hong Kong Hang Seng	German 10-year	NOK	PLN
Coffee			Italy MIB	German 30-year	NZD	RUB
Sugar			Japan TOPIX	Australian 10-year	SEK	TRY
Lean Hogs			Netherlands Amsterdam IDX	Canadian 10-year		ZAR
Live Cattle			Sweden OMX 30	U.K. 10-year		
			Singapore Index			
			U.S. S&P 500			

Data Source: Commodity Research Bureau (CRB), Bloomberg, and DataStream.

Appendix A reports summary statistics of monthly returns for all instruments by commodity sector/asset class. Monthly futures returns are available as early as August 1959 (primarily agriculture commodities). Monthly FX forwards returns begin in February 1973 when major currencies adopted the floating exchange rate regime. The complete coverage of all instruments begins in 2003. Table 2 reports the average volatilities, Sharpe ratios, and pairwise correlations by asset class. Consistent with the findings in the literature, equities and sovereign bonds tend to yield long-term positive returns across countries (average Sharpe ratios are 0.30 and 0.64, respectively), while commodities and currencies may add or detract value over time (average Sharpe ratios are 0.14 and -0.07, respectively). In addition, asset volatilities are dramatically different across asset classes. Commodities, on average, exhibit the highest annual volatility (31%), followed by equity indices (19%) and currencies (12%). The volatility of sovereign bonds (6%) has been about one fifth that of commodities. Table 2 also shows evidence of high correlations within the same asset class (except commodities) and low/negative correlations across asset classes.

Table 2. Average Volatilities, Sharpe Ratios, and Pairwise Correlations by Asset Class

Asset Class	Annual Volatility	Sharpe Ratio	Pairwise Correlation	
			within Asset Class	w/other Asset Class
Commodities	31%	0.14	0.18	0.09
Equity Indices	19%	0.30	0.61	0.09
Sovereign Bonds	6%	0.64	0.66	-0.10
Currencies	12%	-0.07	0.45	0.13

Note: The statistics are calculated based on monthly returns over the sample period August 1959–December 2019.

Portfolio Construction

We create three diversified portfolios to capture time-series momentum, asset-class momentum and cross-sectional momentum. Following the convention used in both the time-series and cross-sectional momentum literature, we focus on the 12-month momentum formation window with a one-month holding period. The results on other momentum formation windows such as one-month and three-month are qualitatively similar and discussed in Appendix C.

Time-series Momentum (TSMOM)

Following Moskowitz, Ooi, and Pedersen (2012), we use the sign of an asset's past 12-month return to determine if the asset is in an upward or downward momentum. A long (short) position of an asset is entered if its past 12-month return is positive (negative). To account for volatility differences across markets, we size each position to have the same ex-ante volatility.[2] Mathematically, an asset i's weight in the portfolio at time t is

$$w_{i,t}^{ts} = sign(12m\_ret_{i,t})\frac{10\%}{N_t \times vol_{i,t}} \quad (1)$$

where $12m\_ret_{i,t}$ is the past 12-month return of asset i, $vol_{i,t}$ is the annual volatility of asset I, and N_t is the number of assets at time t. The scalar of 10% is used to equalize the position risk and is not essential in evaluating empirical results. Easily proven, each position in the portfolio has an ex-ante annual volatility $\frac{10\%}{N_t}$.

[2] The equal volatility approach is a common method to size a trend-following portfolio and is used here for illustration. Baltas (2015), and Yang, Qian, and Belton (2019) show that the risk parity approach provides better diversification than the equal volatility approach.

Asset-Class Momentum (ACMOM)

The ACMOM portfolio is a natural extension of the TSMOM portfolio. Instead of holding long or short positions of individual assets, the ACMOM portfolio holds long or short positions of an entire asset class, depending on whether the asset class is in an upward or downward momentum. To gauge the momentum of an asset class, we first construct the asset class return using an equal-weighting scheme. Mathematically, the return of an asset class I at time t is

$$ret_{I,t} = \frac{1}{N_t^I}\sum\nolimits_{i \in I} ret_{i,t} \qquad (2)$$

where $ret_{i,t}$ is the return of an asset i which belongs to the asset class I, N_t^I is the number of assets within the asset class I at time t. Sovereign bond returns are duration-adjusted to be their 10-year equivalent before averaging so that the bond asset class return is not overly influenced by longer-duration bonds. [3] We then apply the 12-month return rule to the asset class returns and construct the ACMOM portfolio. Mathematically, for asset i in the asset class I, its weight in the portfolio is where $12m\_ret_{I,t}$ is the past 12-month return of asset class I.

$$w_{i,t}^{ac} = sign(12m\_ret_{I,t})\frac{10\%}{N_t \times vol_{i,t}} \qquad (3)$$

Cross-Sectional Momentum (CSMOM)

The CSMOM portfolio holds long or short positions of individual assets, depending on the relative performance of an asset to its asset class. Based on a similar 12-month return rule, an asset i's weight in the CSMOM portfolio is

[3] We also use an equal-volatility weighting approach to calculate asset class returns and find similar results.

$$w_{i,t}^{cs} = sign(\underbrace{12m\_ret_{i,t} - 12m\_ret_{I,t}}_{12-month\ relative\ return})\frac{10\%}{N_t \times vol_{i,t}} \tag{4}$$

Comparing Equations (1), (3), and (4), we can see that the TSMOM, ACMOM, CSMOM portfolios are designed to have the same sizing method such that each position in the portfolio has an ex-ante annual volatility $\frac{10\%}{N_t}$. The only difference lies in the position sign (momentum signal): the position signs (long or short) of TSMOM, ACMOM, and CSMOM are determined by the signs of trailing 12-month returns of an asset, an asset class, and an asset relative to its asset class, respectively. [4]

Clearly, $w_{i,t}^{ts}, w_{i,t}^{ac}$, and $w_{i,t}^{cs}$ are closely related. To see this, we re-write Equation (1) as

$$\begin{aligned} w_{i,t}^{ts} &= sign[12m\_ret_{I,t} + (12m\_ret_{i,t} - 12m\_ret_{I,t})]\frac{10\%}{N_t \times vol_{i,t}} \\ &= \begin{cases} w_{i,t}^{ac}, & \text{if } |12m\_ret_{I,t}| > |12m\_ret_{i,t} - 12m\_ret_{I,t}| \\ w_{i,t}^{cs}, & \text{if } |12m\_ret_{I,t}| < |12m\_ret_{i,t} - 12m\_ret_{I,t}| \end{cases} \end{aligned} \tag{5}$$

In words, an asset TSMOM is determined by the stronger effect of its ACMOM and CSMOM (measured by the magnitude of the 12-month asset class return and relative return, respectively) at any point in time.

Table 3 illustrates the relations among the TSMOM, ACMOM, and CSMOM portfolios using a snapshot as of December 2019. Seen from the table, global equities as an asset class exhibited a strong upward momentum (the 12-month asset class return was around 21%), resulting in long positions of all equity futures in the ACMOM portfolio. The CSMOM portfolio held long positions in countries that had positive 12-month relative returns such as Germany, France, and the U.S., and short positions in countries with negative relative returns, such as Australia, Canada, and Singapore. The TSMOM portfolio held the same equity positions as in the ACMOM portfolio since the magnitude of the 12-month asset class return dominated that of the 12-month relative returns for all equity markets.

As regards the currency sleeve, the ACMOM portfolio held short positions in all currencies due to a negative trailing 12-month return for the asset class (-0.41%). The CSMOM portfolio held long positions in currencies with positive relative returns such as AUD, CHF and JPY, and short in those with negative relative returns,

[4] Note the CSMOM portfolio is not necessarily dollar neutral due to the volatility weighting method. The results are qualitatively similar if we impose dollar neutrality. We also experiment with a more concentrated CSMOM portfolio that holds long (short) positions only within the top (bottom) quantile ranked by relative returns. The results are slightly better.

such as EUR, BRL, and CLP. The TSMOM portfolio held the same positions as the CSMOM portfolio for all the above currencies except AUD, since the magnitude of their 12-month relative returns outweighed that of the asset class return.

Table 3. A Snapshot of TSMOM, ACMOM, and CSMOM Portfolios, December 2019

Asset Class	Asset	12-month Return	12-month Asset Class Return	12-month Relative Return	TSMOM Weight	ACMOM Weight	CSMOM Weight
EQ	Australian SPI 200	20.16%	20.86%	-0.70%	1.39%	1.39%	-1.39%
	Canadian TSX 60	18.68%	20.86%	-2.18%	1.57%	1.57%	-1.57%
	German DAX	23.67%	20.86%	2.81%	1.02%	1.02%	1.02%
	France CAC 40	27.02%	20.86%	6.15%	1.11%	1.11%	1.11%
	Singapore Index	11.53%	20.86%	-9.33%	1.08%	1.08%	-1.08%
	U.S. S&P 500	26.00%	20.86%	5.14%	1.20%	1.20%	1.20%
	...						
FX	AUD	-0.14%	-0.41%	0.27%	-1.60%	-1.60%	1.60%
	CHF	1.60%	-0.41%	2.01%	1.96%	-1.96%	1.96%
	EUR	-2.12%	-0.41%	-1.71%	-2.10%	-2.10%	-2.10%
	JPY	1.03%	-0.41%	1.43%	1.86%	-1.86%	1.86%
	BRL	-2.43%	-0.41%	-2.03%	-0.99%	-0.99%	-0.99%
	CLP	-6.99%	-0.41%	-6.58%	-1.25%	-1.25%	-1.25%
	...						

Note: For illustrative purpose, only 12 out of 66 positions are shown in the table.

Empirical Results

We perform historical simulation of the TSMOM, ACMOM, and CSMOM portfolios from 1970 to 2019 during which the majority of asset classes are available. Each portfolio is rebalanced monthly, based on the month-end momentum signals and volatility estimates. The asset volatilities are estimated using monthly returns based on an expanding window with exponential decay.[5] A two-year learning period is required before a new asset is included in a portfolio. Transaction (rollover and rebalancing) costs are incorporated in our empirical evaluation, as explained in Appendix B. The three portfolios have different realized volatilities, with

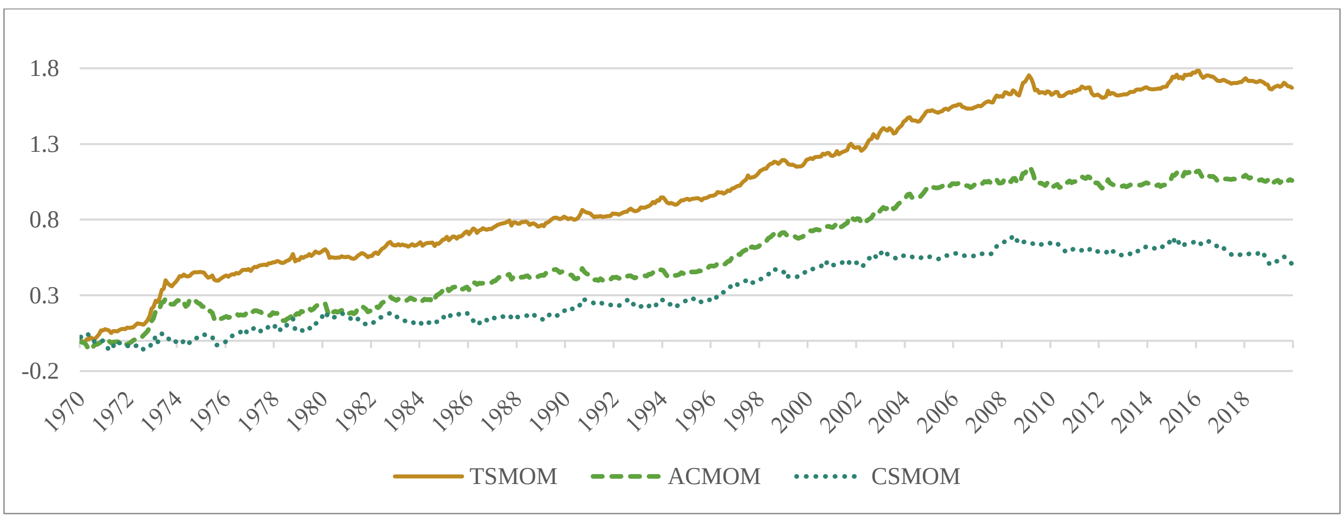
[5] Results are robust to different decay rates, such as 1-, 2-, and 5-year half-life. The results reported in this paper are based on a 2-year half-life decay rate.

ACMOM being the most volatile, followed by TSMOM, and CSMOM being the least. For an equal foot comparison, we scale the portfolio returns to have the same ex-post volatility of 10% per annum. Scalars are 2.96, 2.61, and 4.81 for TSMOM, ACMOM, and CSMOM, respectively.

Returns, Volatilities, and Correlations

Figure 1 plots the (log) cumulative returns of each portfolio. All three portfolios exhibited positive returns over time, although with much weaker performance since 2009 (in particular, the CSMOM portfolio). The pattern of TSMOM performance is broadly consistent with the MF/CTA industry performance, and has been discussed in details in Moskowitz, Ooi, and Pedersen (2012), Hurst, Ooi, and Pedersen (2013), and Yang, Qian, and Bryan (2019). Table 4 reports summary statistics of monthly returns and correlations. TSMOM has a Sharpe ratio of 0.82, superior to both ACMOM and CSMOM (0.54 and 0.28), likely benefiting from a moderate correlation between the two components (0.34). TSMOM is more correlated with ACMOM (0.83) than with CSMOM (0.62), indicating that the asset-class momentum is the more important driver of an asset's time-series momentum.

Figure 1. (Log) Cumulative Returns of Momentum Portfolios



Note: TSMOM, ACMOM, and CSMOM are the returns (net of transaction costs) of the time-series momentum, asset-class momentum, and cross-sectional momentum portfolios, all standardized to 10% volatility per annum. Sample period: 1970–2019.

Table 4. Summary Statistics

Panel A. Returns, Volatilities and Sharpe Ratios

	TSMOM	ACMOM	CSMOM
Annual Excess Return (Ex. Ret.)	8.23%	5.39%	2.84%
Annual Standard Deviation (Std. Dev.)	10%	10%	10%
Sharpe Ratio	0.82	0.54	0.28

Panel B. Monthly Correlations

	TSMOM	ACMOM	CSMOM
TSMOM	1	0.83	0.62
ACMOM		1	0.34
CSMOM			1

Note: Sample period: 1970–2019.

We further perform monthly TSMOM, ACMOM and CSMOM return attributions by asset class by simply aggregating the returns within the same asset class for each portfolio. From Panel A of Table 5, all asset classes in the TSMOM portfolio have delivered decent Sharpe ratios, ranging from 0.39 for equities, to 0.58 for bonds.

The Sharpe ratios by asset class in the ACMOM portfolio are generally lower, but still reasonably good, ranging from 0.25 for equities to 0.36 for bonds. The CSMOM portfolio, on the other hand, has weaker Sharpe ratios (around 0.2 for currencies and bonds, and below 0.2 for commodities and equities). The superiority of the TSMOM portfolio over the CSMOM portfolio is consistent with the evidence documented in Moskowitz, Ooi, and Pedersen (2012).

TABLE 5. Momentum Return Attributions by Asset Class

Panel A. Returns, Volatilities and Sharpe Ratios by Asset Class

	TSMOM				ACMOM				CSMOM			
	CM	EQ	FX	BD	CM	EQ	FX	BD	CM	EQ	FX	BD
Annual Ex. Ret.	2.98%	1.43%	1.89%	2.08%	1.94%	0.98%	1.21%	1.36%	0.59%	0.55%	1.00%	0.77%
Annual Std. Dev.	5.31%	3.67%	4.47%	3.61%	6.08%	3.96%	4.86%	3.82%	6.60%	3.35%	4.63%	3.67%
Sharpe Ratio	0.56	0.39	0.42	0.58	0.32	0.25	0.25	0.36	0.09	0.16	0.22	0.21

Panel B. Monthly Correlations

	TSMOM				ACMOM				CSMOM			
	CM	EQ	FX	BD	CM	EQ	FX	BD	CM	EQ	FX	BD
TSMOM_CM	1.00	0.14	0.25	0.04	**0.72**	0.07	0.20	-0.08	**0.62**	0.18	0.16	0.09
TSMOM_EQ		1.00	0.20	0.10	0.06	**0.87**	0.15	0.08	0.12	**0.41**	0.19	0.01
TSMOM_FX			1.00	0.13	0.15	0.15	**0.83**	0.11	0.14	0.23	**0.57**	0.09
TSMOM_BD				1.00	-0.01	0.07	0.13	**0.85**	-0.01	0.07	0.14	0.10
ACMOM_CM					1.00	0.03	0.11	-0.10	**0.33**	0.13	0.05	0.09
ACMOM_EQ						1.00	0.11	0.08	0.09	0.27	0.19	-0.02
ACMOM_FX							1.00	0.10	0.11	0.18	**0.41**	0.06
ACMOM_BD								1.00	-0.02	0.05	0.14	-0.01
CSMOM_CM									1.00	0.07	0.10	0.00
CSMOM_EQ										1.00	0.09	0.04
CSMOM_FX											1.00	0.02
CSMOM_BD												1.00

Note: The TSMOM, ACMOM, and CSMOM returns by asset class are calculated by simply aggregating the returns within the same asset class for each portfolio. Bold numbers in Panel B indicate correlations higher than 0.3. Sample period: 1970–2019.

Panel B reports monthly correlations among momentum returns across and within different asset classes. For the same momentum style (TSMOM, ACMOM, or CSMOM), the correlations are generally low across asset classes, suggesting diversification benefits from multi-asset momentum investing. Specifically, the maximum correlations across asset classes are 0.25, 0.11, and 0.09 for TSMOM, ACMOM, and CSMOM, respectively. Within the same asset class, TSMOM is correlated with both ACMOM and CSMOM, but more so with ACMOM. For example, for commodities, TSMOM has a correlation of 0.72 with ACMOM, and a correlation of 0.62 with CSMOM. Similar patterns are observed for other asset classes. This observation is consistent with Panel B of Table 4, suggesting that TSMOM is mainly driven by ACMOM.

Note that ACMOM and CSMOM are moderately correlated within commodities (0.33) and currencies (0.41), even though by intuition the two momentum portfolios should not be correlated within the same asset class (absolute momentum vs. relative momentum). This is due to periodical directional exposure in the CSMOM of commodities (for example, energy vs. precious metal) and currencies (e.g., EMFX vs. DMFX). For example, during a bullish commodity cycle, high-beta energy sector generally outperform low-beta precious metal sector. As a result, the CSMOM portfolio likely has net long positions in the energy sector and net short positions in the precious metal sector, creating a directional long exposure in the commodity beta which coincides with positive commodity ACMOM exposure.

Regression Analysis

We now turn to the regression approach to quantify the contribution of momentum components to the TSMOM performance.

Specifically, we estimate the following multivariate regression model:

$$TSMOM_t = \alpha + \sum_i \beta_i Component_{i,t} + \varepsilon_t \qquad (6)$$

where $TSMOM_t$ and $Component_{i,t}$ are the monthly returns of TSMOM and its components at time t. We perform two levels of regressions. The first level is to regress TSMOM on ACMOM and CSMOM, and the second level expands the independent variables to the ACMOM and CSMOM returns by asset class.

Panel A of Table 6 reports the results from the first-level regression. Both ACMOM and CSMOM are significant drivers of TSMOM, with ACMOM exhibiting much greater influence. Specifically, the coefficients (t-statistics) of ACMOM and CSMOM are 0.68 (15.93) and 0.32 (12.38), respectively. Combined, the two momentum components explain around 76% of the variance of TSMOM returns (56% and 20% from ACMOM and CSMOM, respectively). The results also indicate that TSMOM is not fully captured by ACMOM and CSMOM, showing a positive alpha of 0.3% per month with a t-statistic of 4.66.

Panel B of Table 6 reports the results from the more granular level regression. The adjusted R-square slightly increases to 82% (59% and 23% from ACMOM and CSMOM, respectively). Within the ACMOM components, equities, currencies, and bonds contributed comparably with their coefficients around 0.7-0.9 and t-statistics above 12. The coefficient of commodity ACMOM is lower at 0.37, but still quite significant with a t-statistic of 6.29. The CSMOM components, on the other hand, generally have significant but weaker explanatory power (except the commodity CSMOM), as shown by smaller coefficients and t-statistics. The bond CSMOM component, in particular, has the lowest coefficient of 0.13 and t-statistic of 2.35. The alpha component remains significant at 0.22% per month with a t-statistic of 3.99.

Table 6. Regression Analysis

Panel A. Decomposing TSMOM into ACMOM and CSMOM

Dependent Variable	Independent Variables			Adjusted R-square
TSMOM	Intercept	ACMOM	CSMOM	
Coefficient	0.30%**	0.68**	0.32**	76%
T-statistic	4.66	15.93	12.38	
Risk Contribution		56%	20%	

Panel B. Decomposing TSMOM into ACMOM and CSMOM by Asset Class

Dependent Variable	Independent Variables									Adjusted R-square
		ACMOM				CSMOM				
TSMOM	Intercept	CM	EQ	FX	BD	CM	EQ	FX	BD	
Coefficient	0.22**	0.37**	0.82**	0.73**	0.83**	0.41**	0.43**	0.31**	0.13*	82%
T-statistic	3.99	6.29	16.25	12.14	12.22	11.62	5.97	6.41	2.35	
Risk Contribution		7%	17%	22%	13%	11%	4%	7%	1%	

*Note: * and ** indicate statistical significance at the 5% and 1% level, respectively. Risk contribution is defined as the contribution of each component to the variance of TSMOM returns. Sample period: 1970–2019.*

Combining the results from the correlation and regression analysis, we can conclude that while both ACMOM and CSMOM are important drivers of TSMOM, the former has been the most dominant factor behind TSMOM, explaining over 50% of the variance of TSMOM returns. There is also a significant alpha in TSMOM in excess of ACMOM and CSMOM, which presumably results from the low correlations among the ACMOM and CSMOM components (the diversification benefits).

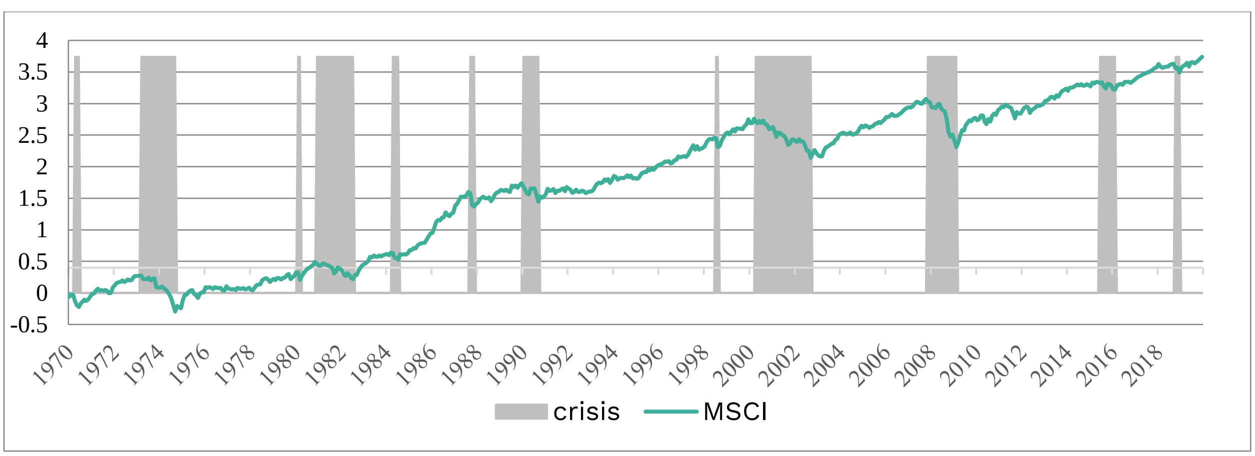
Practical Applications

Crisis Alpha and Risk Premia

One desired property of TSMOM is that it not only yields positive returns over normal periods (risk premia), but also provides downside protection during crisis periods (crisis alpha) (Greyserman and Kaminski 2014). In this section, we investigate whether the characteristics of crisis alpha and risk premia are universally shared across its ACMOM and CSMOM components.

Following Greyserman and Kaminski (2014), we define crisis periods as when the MSCI World Total Return Index (MSCI) was down below a threshold from peak to trough. For illustration, we use a threshold of -10% which results in 12 crisis periods over our sample period (1970–2019). The results are qualitatively similar to other threshold parameters. Figure 2 plots the (log) cumulative returns of MSCI as well as the identified crisis periods (highlighted in grey). Among the most severe ones are the 2007-2008 Global Financial Crisis (GFC), the 2000-2002 Dot-com Bubble Burst, and the 1973-1974 Stagflation.

Figure 2. (Log) Cumulative Returns of MSCI



Note: Crisis periods are defined as when the MSCI World Total Return Index was down more than 10% from peak to trough. Sample period: 1970–2019.

Table 7 reports performance statistics of MSCI, TSMOM, and ACMOM/CSMOM by asset class during crisis and normal periods. Consistent with the literature, we find TSMOM provided significant returns during both crisis and normal periods. Specifically, over the 120-month crisis periods, TSMOM yielded an average return of 1.32% per month with a t-statistic of 4.03, compared to -2.83% and -6.23 of MSCI. Over the 480-month normal periods, TSMOM yielded an average of 0.53% per month with a t-statistic of 4.33, compared to 1.60% and 10.14 of MSCI. The hit-ratios (frequency of positive-return months) of TSMOM during crisis/normal periods were 63% and 60%, respectively, well above the 50% threshold.

Table 7. Crisis Alpha vs. Risk Premia

			ACMOM				CSMOM			
	MSCI	TSMOM	CM	EQ	FX	BD	CM	EQ	FX	BD
Crisis Periods: 120 months										
Monthly Return	-2.83%**	1.32%**	0.50%*	-0.09%	0.35%*	0.01%	0.12%	-0.08%	0.17%	0.15%
T-Statistic	-6.23	4.03	2.28	-0.61	2.27	0.10	0.55	-0.81	1.34	1.44
Hit-Ratio		63%	61%	48%	61%	53%	58%	38%	53%	58%
Normal Periods: 480 months										
Monthly Return	1.60%**	0.53%**	0.08%	0.13%**	0.04%	0.14%**	0.03%	0.08%	0.06%	0.04%
T-Statistic	10.14	4.33	1.09	2.85	0.64	2.96	0.40	1.75	0.99	0.91
Hit-Ratio		60%	52%	59%	54%	57%	50%	51%	53%	52%

*Note: * and ** indicate statistical significance at the 5% and 1% level, respectively. Hit-ratio is the frequency of positive-return months out of total months. Sample period: 1970–2019.*

The TSMOM components, however, exhibited heterogeneities in terms of crisis alpha and risk premia properties. During crisis periods, only two components (the ACMOM of commodities and currencies) provided significant crisis alpha (average monthly returns of 0.50% and 0.35% with t-statistics of 2.28 and 2.27, respectively). The crisis alpha of other components were either insignificant or negative. In particular, the ACMOM and CSMOM of equities on average delivered negative returns during crisis periods (average monthly returns of -0.09% and -0.08%, respectively). These observations are in contrast with the beliefs of some investors that the crisis alpha of momentum/trend-following strategies mainly came from riding on the negative equity momentum. During normal periods, while all ACMOM and CSMOM components yielded positive returns, the ACMOM of equities and bonds appeared to provide the most significant risk premia as measured by t-statistics (average monthly returns of 0.13% and 0.14% with t-statistics of 2.85 and 2.96, respectively).

To further understand the drivers of crisis alpha, we report in Table 8 the cumulative returns of TSMOM as well as its components during crisis periods. The duration of crisis periods ranged from two months (February 1980–March 1980; July 1998–August 1998) to 30 months (April 2000–September 2002), with an average duration of about 10 months. During these crisis periods, MSCI detracted an average of -24.3%, while TSMOM yielded an average of 14.7% with the ACMOM of commodities and currencies contributed the most (5.4% and 3.1%, respectively).

During the three worst drawdown periods (1. GFC: November 2007–February 2009; 2. Dot-com Bubble Burst: April 2000–September 2002; and 3. Stagflation: March 1973–September 1974), MSCI detracted over 40% in each period. On the other end, TSMOM recorded its best performance during these three periods, up more than 35% each. During Crisis 1 and 2, a majority of the momentum components contributed positive returns. During Crisis 3, however, the ACMOM of commodities contributed the majority of returns, thanks to its net long commodity exposure amid the Stagflation environment.

Table 8. Cumulative Performance during Crisis Periods

Crises Periods				ACMOM				CSMOM			
Start Month-End Month	Duration (Months)	MSCI	TSMOM	CM	EQ	FX	BD	CM	EQ	FX	BD
11/2007-02/2009	16	-53.6%	35.4%	-3.4%	8.9%	7.6%	7.3%	8.2%	-1.3%	1.8%	-0.6%
04/2000-9/2002	30	-46.2%	46.2%	-2.5%	11.2%	9.4%	9.2%	4.6%	-0.3%	13.3%	6.3%
03/1973-09/1974	19	-43.4%	54.1%	39.9%	-0.7%	-3.6%	-12.0%	3.3%	-6.7%	-6.0%	6.4%
01/1990-09/1990	9	-25.4%	11.0%	4.3%	0.5%	2.2%	-0.2%	10.0%	2.0%	3.9%	3.0%
12/1980-07/1982	20	-23.8%	15.4%	14.0%	-0.4%	8.5%	-5.5%	-3.7%	-2.1%	0.0%	2.6%
09/1987/-11/1987	3	-20.8%	-1.1%	3.8%	-8.0%	2.6%	-0.8%	-0.9%	0.7%	0.4%	-0.1%
04/1970-06/1970	3	-17.8%	7.1%	0.9%	-4.9%	0.0%	-2.8%	-5.5%	3.6%	0.0%	1.5%
07/1998-08/1998	2	-13.5%	3.9%	4.8%	-4.3%	2.5%	2.3%	0.0%	-0.5%	2.6%	1.3%
10/2018-12/2018	3	-13.3%	-4.3%	1.6%	-1.0%	0.7%	-2.4%	-6.6%	-0.7%	-3.7%	-2.1%
06/2015-02/2016	9	-11.6%	10.0%	7.1%	-9.1%	5.5%	3.2%	3.9%	-1.4%	1.2%	-1.7%
02/1980-03/1980	2	-11.3%	-3.1%	-6.8%	-1.9%	-3.9%	4.0%	-3.8%	-1.7%	1.0%	2.2%
04/1984-07/1984	4	-11.3%	2.2%	0.6%	-1.1%	6.1%	-0.2%	3.1%	-0.8%	4.2%	-1.2%
Mean	10	-24.3%	14.7%	5.4%	-0.9%	3.1%	0.2%	-1.5%	-0.3%	1.1%	0.5%

TSMOM experienced (moderate) losses during three out of the 12 crisis periods: September 1987–November 1987 (TSMOM -1.1% vs. MSCI -20.8%), October 2018–December 2018 (TSMOM -4.3% vs. MSCI-13.3%) and February 1980–March 1980 (TSMOM -3.1% vs. MSCI -11.3%). A common feature of the three periods is their short length (typically two–three months), which made it challenging to capitalize on the 12-month momentum.

Explaining MF/CTA Performance

As shown in Hurst, Ooi, and Pedersen (2013), TSMOM accounts for a significant portion of the MF/CTA industry performance as shown by significant regression coefficients and high R-squares. We investigate in this section how each momentum component has contributed to the industry performance, as well its evolution over time.

We use three commonly referenced MF/CTA indices to measure the industry performance: BTOP50 Index from BarclayHedge (BTOP), SG Trend Index from Societe Generale (SGTR), and HFR Systematic Macro/CTA Index from Hedge Fund Research (HFRM). All three indices are manager-based return indices that seek to represent the MF/CTA industry performance. BTOP has the longest history from 1987, followed by SGTR from 2000, and HFRM from 2005.

Table 9 reports summary statistics of indices' performance, as well as correlations among the indices and our momentum strategies. All indices have yielded positive returns over their live periods with Sharpe ratios from 0.24 to 0.41. SGTR exhibited the highest annualized volatility of around 14%, while the annualized volatilities of the other two were around 9–10%. These indices are highly correlated among themselves (correlations from 0.85 to 0.97), likely due to two reasons. First, there is an overlap of managers selected into these indices (typically the largest MF/CTA managers). Second, managers may follow similar momentum strategies, as shown by the high correlations between the indices and our momentum strategies (correlations from 0.34 to 0.56).

Table 9. Summary Statistics of MF/CTA Indices

Panel A. Returns, Volatilities, and Sharpe Ratios

	BTOP	SGTR	HFRM
Inception	01/1987	01/2000	01/2005
Annual Excess Return	3.90%	4.02%	2.18%
Annual Standard Deviation	9.54%	13.90%	9.20%
Sharpe Ratio	0.41	0.29	0.24

Panel B. Monthly Correlations

	BTOP	SGTR	HFRM	TSMOM	ACMOM	CSMOM
BTOP	1.00	0.97	0.85	0.50	0.44	0.34
SGTR		1.00	0.87	0.56	0.50	0.37
HFRM			1.00	0.54	0.46	0.41

Note: Sample periods are 1987-2019, 2000-2019, and 2005-2019 for BTOP, SGTR, and HFRM, respectively.

Similar to the previous regression analysis, we regress monthly returns of each index on the returns of ACMOM and CSMOM components. [6] As shown in Table 10, the majority of the ACMOM components have significant coefficients. In particular, the ACMOM of bonds consistently appears to be the most significant driver behind these indices' performance with t-statistics equal to 5.63, 4.56, and 4.06 for BTOP, SGTR, and HFRM, respectively. It suggests that MF/CTA managers have been riding the bullish momentum of global bonds over the last 30+ years. The CSMOM of commodities and currencies, on the other hand, consistently appear to be important performance drivers among the CSMOM components. This may be due to managers capitalizing on (directional) sector momentum (for example, energy vs. precious metal; EMFX vs. DMFX) within commodities and currencies. The CSMOM of equities and bonds have contributed insignificant or even negative returns to the index performance. The intercept terms are insignificant across indices, and the adjusted R-square ranges from 24% to 41%.

[6] Given the high correlations among indices, the differences in estimation results across indices are more likely due to different sample periods rather than underlying data generating processes.

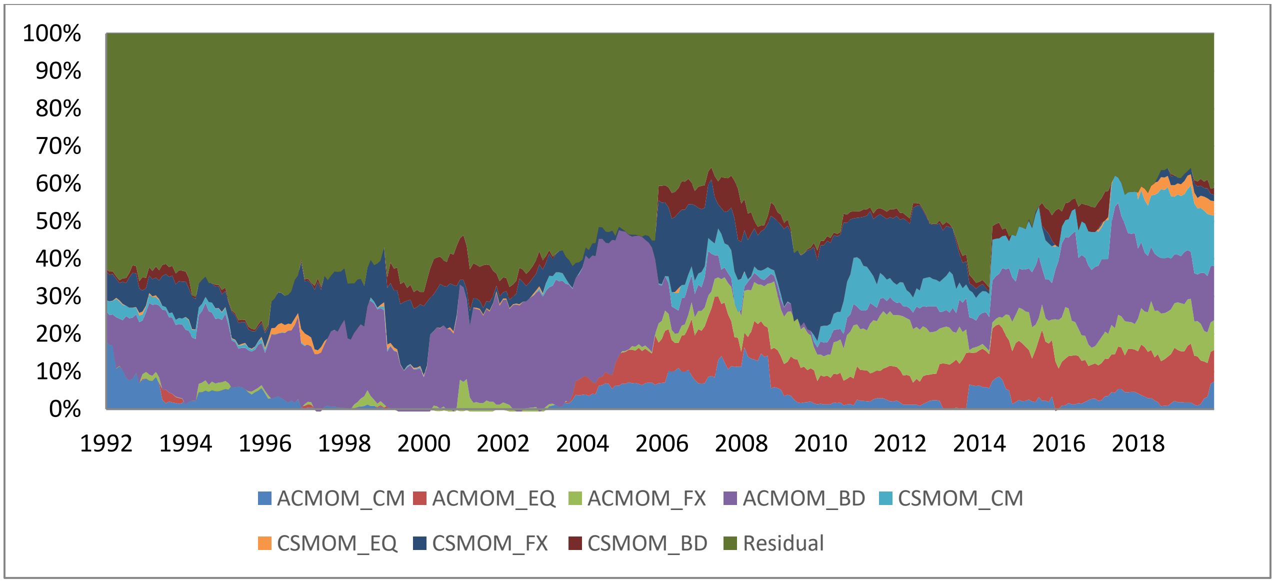
Table 10. Decomposing MF/CTA Index Performance

Dependent Variable	Intercept	ACMOM CM	ACMOM EQ	ACMOM FX	ACMOM BD	CSMOM CM	CSMOM EQ	CSMOM FX	CSMOM BD	Adjusted R-square
BTOP	0.10 (0.91)	0.40** (3.17)	0.24* (2.36)	0.12 (1.31)	0.82** (5.63)	0.21** (2.68)	-0.05 (-0.22)	0.47** (2.94)	0.08 (0.79)	25%
SGTR	-0.01 (-0.03)	0.50** (2.87)	0.91** (5.13)	0.23 (1.73)	1.21** (4.56)	0.52** (3.08)	0.26 (0.73)	0.43 (1.23)	0.21 (1.12)	38%
HFRM	0.08 (0.60)	0.27 (1.48)	0.52** (3.63)	0.19* (2.09)	0.83** (5.06)	0.55** (4.09)	0.25 (0.86)	0.46* (2.42)	-0.07 (-0.52)	40%

*Note: The numbers in parenthesis are t-statistics. * and ** indicate statistical significance at the 5% and 1% level, respectively. Regression periods are 1987-2019, 2000-2019, and 2005-2019 for BTOP, SGTR, and HFRM, respectively.*

One important characteristic of these indices is their time-varying constituents. Generally they are reconstituted on a fixed (annual) frequency, with managers being included or removed based on preset criteria (AUM, performance, etc.). The reconstitution could potentially lead to significant changes in the momentum strategies underneath these indices. To see the dynamics of the underlying drivers, we also run rolling regressions of the indices on the momentum components, allowing regression coefficients to change over time. Figure 3 plots the time-varying risk contributions of each momentum component, as well as of the residual to the BTOP index, based on a five-year rolling window. Risk contribution is defined as the contribution of each component to the variance of the index returns. Results are similar to other rolling window lengths, as well as for SGTR and HFRM.

Figure 3. Explaining BTOP: Risk Contribution from a 5-Year Rolling Regression



Note: Risk contribution is defined as the contribution to the variance of the BTOP index returns.

A couple of observations can be made from Figure 3. First, while the residual (accounting for omitted factors such as different momentum horizons, complex momentum signals, etc.) has contributed the majority of the index risk, its risk contribution has exhibited dwindling magnitude over time. Specifically, the risk contribution from the residual was in the range of 60%-80% in the 1990s, but has declined to about 40% by 2019. Correspondingly, the sum of the risk contributions from our momentum components (equivalently, the R-square) has increased from around 20%-40% in the 1990s to 60% by 2019. This indicates MF/CTA managers may have become more exposed to common momentum factors, and hence the diversification benefits from investing in multi-managers may have diminished.

Second, the ACMOM of bonds has consistently been the dominant risk contributor among the momentum components, consistent with the results in Table 10. The risk contributions from other ACMOM components have increased steadily since the mid-2000s. On the other hand, the risk contributions from the CSMOM components (except commodities) have declined lately, suggesting that managers have reduced exposure to CSMOM possibly due to its poor (even negative) performance of CSMOM since the late 2000s (as shown in Figure 1). In particular, the CSMOM of currencies used to explain a meaningful portion of the index returns (specifically, during the 1990s and 2000s), but has become marginal during the 2010s.

Conclusion

Time-series momentum and cross-sectional momentum have attracted great attention from both academia and practitioners. While unique in their own theoretical underpinnings and practical applications, they are closely related. Generally, time-series momentum is found to subsume cross-sectional momentum. In this paper, we incorporate asset-class momentum to bridge the gap between time-series momentum and cross-sectional momentum. Using an analytic framework, we show that both asset-class momentum and cross-sectional momentum are important components, but the former has played a predominant role in explaining time-series momentum over the past half century.

We further apply the framework to analyzing the crisis alpha/risk premia characteristics of time-series momentum, as well as explaining the MF/CTA industry performance. We find that the crisis alpha of time-series momentum over the past half century most evidently came from the asset-class momentum of commodities and currencies. This is in contrast with the beliefs of some investors that the crisis alpha of trend-following strategies mainly came from riding on the negative equity momentum. On the other hand, the asset-class momentum of equities and bonds provided the most significant returns (risk premia) during normal periods. Our analysis of commonly referenced MF/CTA indices shows that the industry performance has been increasingly exposed to generic time-series momentum (in particular, asset-class momentum), implying that the diversification benefits from investing in multi-managers may have reduced. Our analytical framework has important implications for practitioners. From a risk management perspective, momentum investors may use the decomposition framework to identify the key return/risk drivers in their portfolios. While a typical momentum strategy trades a large number of markets to achieve diversification benefits, our analysis shows that the return/risk drivers can be largely reduced to a handful of asset-class and cross-sectional momentum components (factors). The reduced-form factor analysis is likely to be more relevant and efficient now than before as today's markets are increasingly correlated (and so are the momentum effects across markets).

From a strategy design perspective, by decomposing time-series momentum into a reduced number of directly observable components, we can model each component separately and combine them into an optimal momentum portfolio. Intuitively, different momentum components may have their own drivers and follow distinct cycles. For example, the bullish asset-class momentum of bonds reflects the trend of global disinflation, and may persist as long as global inflation continues to drift lower. On the other hand, the cross-sectional momentum of country equity indices is mainly driven by cross-country divergence of economic fundamentals. Its effect may be weakened in global integration and strengthened in global disintegration. By identifying the corresponding drivers, we may be able to capture (and time) individual momentum components better and form a more optimal momentum portfolio than a simple time-series momentum portfolio.

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Appendix A. Summary Statistics of Monthly Returns

Futures/Forwards	Data Start	Ann. Mean	Ann. St. Dev.	Sharpe Ratio
Agriculture Commodities				
Soybean Oil	08/1959	6.29%	29.61%	0.21
Corn	08/1959	-2.64%	24.02%	-0.11
Soybean Meal	08/1959	10.51%	31.35%	0.34
Soybean	08/1959	4.98%	25.87%	0.19
Wheat	08/1959	-2.66%	25.53%	-0.10
Cocoa	08/1959	4.12%	30.79%	0.13
Cotton	08/1959	2.89%	24.24%	0.12
Coffee	06/1973	4.57%	36.71%	0.12
Sugar	08/1959	-2.74%	44.32%	-0.06
Lean Hogs	04/1966	4.84%	27.03%	0.18
Live Cattle	01/1965	4.78%	17.34%	0.28
Energy Commodities				
Brent Crude	08/1989	13.30%	33.39%	0.40
WTI Crude	05/1983	9.47%	35.24%	0.27
Heating Oil	12/1978	13.62%	34.88%	0.39
Gas Oil	07/1986	11.91%	32.23%	0.37
Natural Gas	05/1990	-2.03%	55.76%	-0.04
Gasoline	03/1976	8.53%	39.32%	0.22
Metal Commodities				
Copper	08/1959	9.79%	27.42%	0.36
Aluminum	12/1988	-4.63%	20.14%	-0.23
Nickel	02/1989	-0.20%	33.55%	-0.01
Zinc	02/1992	-2.33%	24.36%	-0.10
Gold	09/1971	4.54%	20.07%	0.23
Silver	07/1967	3.15%	33.06%	0.10
Equity Indices				
Australian SPI 200	06/1992	4.16%	12.85%	0.32
Canadian TSX 60	02/1982	3.71%	14.71%	0.25
German DAX	11/1959	3.86%	19.01%	0.20
Spain IBEX 35	02/1987	4.87%	21.50%	0.23
France CAC 40	08/1987	5.70%	19.44%	0.29
U.K. FTSE 100	02/1984	4.53%	15.11%	0.30
Hong Kong Hang Seng	09/1964	11.98%	30.82%	0.39
Italy MIB	02/1998	2.58%	21.40%	0.12
Japan TOPIX	08/1959	4.17%	17.67%	0.24
Netherlands Amsterdam IDX	02/1983	8.12%	19.37%	0.42
Sweden OMX 30	01/1987	9.11%	21.65%	0.42
Singapore Index	02/1988	6.09%	22.45%	0.27

U.S. S&P 500	08/1959	5.99%	14.59%	0.41
Sovereign Bonds				
U.S. 2-year	07/1961	2.66%	2.81%	0.95
U.S. 5-year	07/1961	3.27%	5.00%	0.65
U.S. 10-year	07/1961	3.47%	6.96%	0.50
U.S. 30-year	09/1971	4.04%	10.48%	0.39
German 2-year	04/1997	0.81%	1.19%	0.68
German 5-year	11/1991	2.78%	3.03%	0.92
German 10-year	12/1990	4.29%	5.07%	0.84
German 30-year	11/2005	7.25%	12.06%	0.60
Australian 10-year	10/1987	3.49%	7.90%	0.44
Canadian 10-year	10/1989	3.58%	5.87%	0.61
U.K. 10-year	12/1982	3.37%	7.33%	0.46
DM Currencies				
AUD	02/1984	-0.08%	11.53%	-0.01
CAD	02/1973	-0.33%	6.73%	-0.05
CHF	02/1973	3.52%	11.91%	0.30
EUR	02/1975	0.12%	10.29%	0.01
GBP	02/1973	-0.76%	9.91%	-0.08
JPY	02/1973	2.79%	11.19%	0.25
NOK	02/1973	-0.08%	10.52%	-0.01
NZD	02/1986	1.37%	11.71%	0.12
SEK	01/1993	-0.43%	10.93%	-0.04
EM Currencies				
BRL	02/1999	-1.74%	17.09%	-0.10
CLP	02/1988	-3.06%	9.93%	-0.31
CZK	07/1993	1.66%	11.51%	0.14
HUF	04/1998	-0.63%	13.10%	-0.05
KRW	02/1998	1.96%	11.92%	0.16
MXN	02/1996	-3.41%	10.20%	-0.33
PLN	07/1993	-2.12%	12.37%	-0.17
RUB	02/1999	-3.92%	12.63%	-0.31
TRY	02/2002	-7.18%	15.22%	-0.47
ZAR	02/1980	-5.94%	15.07%	-0.39

Data Source: Commodity Research Bureau (CRB), Bloomberg, and DataStream.

Appendix B. Transaction Costs Assumptions

Trading futures/forwards generally involves two types of transaction costs: rollover costs and rebalancing costs. Rollover costs refer to the costs associated with rolling over an open future/forward position from the front month contract that is expiring to a further-out contract (typically the next nearest contract). Other things equal, a portfolio with higher leverage (more open positions) incurs higher rollover costs. Rebalance costs refer to costs associated with changes in portfolio positions (due to changes of momentum signals, volatility and correlation estimates, etc.). A portfolio with faster-moving momentum signals or volatility/correlation estimates leads to higher rebalance costs.

In each type of cost, there are both explicit and implicit components. Explicit costs include commissions, exchange fees, clearing fees, etc. These are generally small for trading futures / forwards. Implicit costs include bid-ask spreads, execution delay, market impact, etc. These costs tend to vary across markets and time periods, and can be potentially significant for high-leverage and high turnover portfolios. A full-scope discussion on transaction costs is not the focus of this paper. We hereafter follow the assumptions made in Baltas and Kosowski (2015) and Hurst, Ooi and Pedersen (2017). Specifically, we calculate the rollover and the rebalancing costs as follows:

$$\text{Rollover costs}_t = \sum_{i=1}^{N} |w_{i,t}| \cdot \theta_i \qquad \text{(B1)}$$

$$\text{Rebalancing costs}_t = \sum_{i=1}^{N} |w_{i,t} - w_{i,t-1}| \cdot \gamma_i \qquad \text{(B2)}$$

where $w_{i,t}$ is asset i's weight in the momentum portfolio at t, θ_i is the rollover costs for asset i, γ_i is the rebalancing cost for asset i. The exhibit below shows the rollover and rebalancing cost assumptions by asset class and time period. In general, commodity futures have the highest trading costs, followed by emerging market currencies and global equity index futures. Sovereign bond futures and developed markets currencies have the lowest trading costs.

Asset Class	Time Period	Average Rollover Costs (Basis Points Per Annum)	Average 1-Way Rebalancing Costs (Basis Points Per Transaction)
Commodities	prior 1993	180	60
	1993-2002	60	20
	post 2003	30	10
Equity Indices	prior 1993	72	36
	1993-2002	24	12
	post 2003	12	6
Sovereign Bonds	prior 1993	12	6
	1993-2002	4	2
	post 2003	2	1
DM Currencies	prior 1993	36	18
	1993-2002	12	6
	post 2003	6	3
EM Currencies	prior 1993	90	30
	1993-2002	30	10
	post 2003	15	5

Appendix C. Robustness to Momentum Horizons

In this Appendix, we check the robustness of our results to different momentum horizons. Specifically, in addition to the 12-month look-back window, we also use one-month and three-month look-back windows as the momentum formation horizons. Methodologically, we simply replace the 12-month return signals in Equation (1), (3) and (4) with the one-month and three-month return signals, while keeping other aspects (one-month holding period, volatility estimates, etc.) the same. The one-month and three-month windows have been used in Hurst, Ooi, and Pedersen (2013) to capture short- and medium-term momentum effects.

Appendix C1 reports the returns, volatilities and Sharpe ratios of one-month and three-month momentum strategies. In terms of risk-adjusted returns, the one-month and three-month horizons yielded lower Sharper ratios compared to the 12-month horizon (0.37 and 0.61 compared to 0.82). The declining efficacy of momentum signals with shorter look-back window length is in line with the findings in the literature (Hurst, Ooi, and Pedersen 2013; Duke, Harding, and Land 2013). Similar to the findings in the 12-month momentum strategy, the ACMOM components in general are more profitable than their CSMOM counterparts. For example, for the three-month momentum strategy, the Sharpe ratios of ACMOM range from 0.11 (commodities) to 0.28 (bonds), while those of CSMOM ranging from -0.18 (equities) to 0.08 (bonds). Note that there appear to be one-month cross-sectional reversal effects across asset classes (particular for equity indices), similar to the short-term reversal effects in stocks.

TABLE C1. Returns, Volatilities and Sharpe Ratios

Panel A. 1-Month Momentum

		ACMOM				CSMOM			
	TSMOM	CM	EQ	FX	BD	CM	EQ	FX	BD
Annual Ex. Ret.	3.64%	0.13%	0.59%	-0.20%	1.34%	-0.86%	-1.18%	-0.03%	-0.64%
Annual Std. Dev.	10%	5.76%	3.69%	4.55%	3.55%	6.87%	3.11%	4.18%	3.52%
Sharpe Ratio	0.37	0.02	0.16	-0.04	0.38	-0.13	-0.38	-0.01	-0.18

Panel B. 3-Month Momentum

		ACMOM				CSMOM			
	TSMOM	CM	EQ	FX	BD	CM	EQ	FX	BD
Annual Ex. Ret.	6.10%	0.60%	0.90%	1.06%	0.99%	0.23%	-0.56%	0.30%	0.29%
Annual Std. Dev.	10%	5.69%	3.69%	4.54%	3.58%	6.98%	3.08%	4.32%	3.70%
Sharpe Ratio	0.61	0.11	0.24	0.23	0.28	0.03	-0.18	0.07	0.08

Note: Sample period: 1970–2019.

Appendix C2 reports the results from regressing monthly TSMOM returns on their components for the one-month and three-month momentum strategies. Consistent with the 12-month momentum case, all ACMOM and CSMOM components have significant explanatory power for the TSMOM returns, with their t-statistics significant at the 1% level and the adjusted R-square at least 80%. Again, the ACMOM components appear to be the more important drivers of TSMOM, as seen from their higher t-statistics and risk contributions. For the one-month and the three-month momentum strategies, the ACMOM components combined explained 56% and 62% of the variance of TSMOM returns, compared to 24% and 21% for the CSMOM components. The alpha coefficients are significant at the 1% level for both the one-month and three-month momentum strategies.

Table C2. Regression Analysis: Decomposing TSMOM into ACMOM and CSMOM

Panel A. 1-Month Momentum

Dependent Variable	Independent Variables									
TSMOM	Intercept	ACMOM				CSMOM				Adjusted R-square
		CM	EQ	FX	BD	CM	EQ	FX	BD	
Coefficient	0.23**	0.49**	0.73**	0.73**	0.96**	0.45**	0.38**	0.45**	0.15**	80%
T-statistic	4.06	7.89	7.57	11.68	12.99	12.52	3.97	6.72	3.09	
Risk Contribution		10%	13%	18%	14%	12%	2%	9%	1%	

Panel B. 3-Month Momentum

Dependent Variable	Independent Variables									
TSMOM	Intercept	ACMOM				CSMOM				Adjusted R-square
		CM	EQ	FX	BD	CM	EQ	FX	BD	
Coefficient	0.22**	0.48**	0.95**	0.65**	0.87**	0.37**	0.28**	0.44**	0.17**	83%
T-statistic	4.55	7.79	12.41	10.00	17.85	9.99	3.56	8.73	3.83	
Risk Contribution		12%	21%	16%	13%	10%	2%	8%	1%	

Note: * *and* ** *indicate statistical significance at the 5% and 1% level, respectively. Risk contribution is defined as the contribution of each component to the variance of TSMOM returns. Sample period: 1970–2019.*

Appendix C3 reports performance statistics of TSMOM and its ACMOM/CSMOM components during crisis and normal periods. For both the one-month and three-month momentum horizons, TSMOM provided significant crisis alpha with a t-statistic of 2.83 and 2.67, respectively. Again, the majority of the crisis alpha came from the ACMOM components (in particular, commodities and currencies). The CSMOM components yielded either smaller or negative crisis alpha (in particular, equities). During normal periods, the three-month TSMOM yielded significant risk premia (0.38% per month with a t-statistic of 3.42) of which the ACMOM of bonds and equities contributed the majority. The one-month TSMOM, on the other hand, only yielded insignificant risk premia (0.14% per month with a t-statistic of 1.16). Among its components, the ACMOM of bonds and equities contributed the most, while the other components detracted value.

Table C3. Crisis Alpha vs. Risk Premia

Panel A. 1-Month Momentum

			ACMOM				CSMOM			
	MSCI	TSMOM	CM	EQ	FX	BD	CM	EQ	FX	BD
Crisis Periods: 120 months										
Monthly Return	-2.83%**	0.97%**	0.25%	0.02%	0.23%	0.16%	-0.07%	-0.05%	0.19%	-0.01%
T-Statistic	-6.23	2.83	1.18	0.15	1.56	1.41	-0.36	-0.69	1.42	-0.06
Hit-Ratio		54%	48%	49%	57%	56%	42%	40%	59%	48%
Normal Periods: 480 months										
Monthly Return	1.60%**	0.14%	-0.05%	0.06%	-0.07%	0.10%*	-0.07%	-0.11%**	-0.05%	-0.07%
T-Statistic	10.14	1.16	-0.73	1.35	-1.29	2.27	-0.82	-2.63	-0.88	-1.48
Hit-Ratio		60%	48%	56%	46%	54%	46%	41%	45%	44%

Panel B. 3-Month Momentum

	MSCI	TSMOM	ACMOM CM	ACMOM EQ	ACMOM FX	ACMOM BD	CSMOM CM	CSMOM EQ	CSMOM FX	CSMOM BD
Crisis Periods: 120 months										
Monthly Return	-2.83%**	1.01%**	0.33%	0.08%	0.28%	-0.03%	0.22%	-0.22%*	0.04%	0.02%
T-Statistic	-6.23	2.67	1.58	0.58	1.91	-0.23	1.00	-2.57	0.31	0.22
Hit-Ratio		57%	60%	48%	55%	52%	48%	31%	52%	49%
Normal Periods: 480 months										
Monthly Return	1.60%**	0.38%**	-0.02%	0.07%	0.04%	0.11%*	-0.03%	0.00%	0.02%	0.02%
T-Statistic	10.14	3.42	-0.30	1.77	0.74	2.49	-0.36	-0.05	0.37	0.51
Hit-Ratio		56%	49%	58%	51%	56%	47%	47%	51%	49%

Note: * *and* ** *indicate statistical significance at the 5% and 1% level, respectively. Hit-ratio is the frequency of positive-return months out of total months. Sample period: 1970–2019.*

In summary, the crisis alpha and risk premia properties of the one-month and three-month momentum strategies are broadly consistent with those of the 12-month momentum. The key difference is a weaker risk premia for the short-term one-month momentum, mainly due to some reversal effects in its components (cross-sectional reversal in equities, in particular).

Appendix C4 reports the results from regressing monthly MF/CTA index returns on the one-month and three-month momentum components. Similar to the 12-month momentum case, the ACMOM of bonds was the most consistent contributor among the ACMOM components to the index returns, with coefficients mostly significant at the 1% and 5% level. Among the CSMOM components, currencies was the dominant driver (particularly for the three-month momentum), followed by commodities. The evidence also suggests that the industry has become less exposed to the one-month short-term momentum over time. Using the HFRM index as an example (its regression results will reflect the pattern over the most recent periods given its shortest history). The adjusted R-square drops from 40% for the 12-month momentum (Table 10), to 30% and 17% for the three-month and one-month momentum, respectively. The declining industry exposure to short-term momentum is likely a result from the disappointing momentum performance at the short-term horizon.

In summary, the patterns observed at the one-month and three-month momentum are broadly consistent with those of the 12-month momentum. In addition, we find weaker efficacy for shorter-term momentum (the one-month momentum, in particular), consistent with the evidence documented in the literature. As a result, the MF/CTA industry has become less exposed to short-term momentum.

Table C4. Decomposing MF/CTA Index Performance

Panel A. 1-Month Momentum

Dependent Variable	Independent Variables									Adjusted R-square
	Intercept	ACMOM				CSMOM				
		CM	EQ	FX	BD	CM	EQ	FX	BD	
BTOP	0.36^{**} (2.95)	0.25 (1.92)	0.10 (0.83)	0.31^{**} (2.76)	0.65^{**} (3.95)	0.32^{**} (3.20)	0.23 (1.10)	0.68^{**} (4.72)	-0.08 (-0.64)	26%
SGTR	0.34 (1.56)	0.50^{*} (2.10)	0.30 (1.22)	0.37^{*} (2.26)	0.76^{*} (2.26)	0.44^{**} (2.69)	0.14 (0.25)	0.65^{*} (2.40)	-0.13 (-0.59)	20%
HFRM	0.21 (1.25)	0.37 (1.85)	0.21 (1.00)	0.16 (1.29)	0.36 (1.77)	0.51^{**} (3.65)	0.14 (0.34)	0.29 (1.33)	-0.13 (-0.82)	17%

Panel B. 3-Month Momentum

Dependent Variable	Independent Variables									Adjusted R-square
	Intercept	ACMOM				CSMOM				
		CM	EQ	FX	BD	CM	EQ	FX	BD	
BTOP	0.18 (1.57)	0.47^{**} (3.47)	0.19 (1.67)	0.16 (1.35)	0.71^{**} (4.63)	0.19^{*} (2.47)	-0.10 (-0.56)	0.92^{**} (6.70)	-0.10 (-0.82)	32%
SGTR	0.19 (0.95)	0.80^{**} (3.96)	0.42 (1.56)	0.13 (0.66)	1.05^{**} (3.39)	0.41^{**} (2.68)	0.00 (0.01)	1.06^{**} (3.82)	-0.05 (-0.23)	33%
HFRM	0.13 (0.84)	0.31 (1.50)	0.07 (0.39)	0.27 (1.96)	0.57^{**} (3.08)	0.45^{**} (3.52)	-0.09 (-0.21)	0.72^{**} (3.28)	-0.06 (-0.39)	30%

Note: The numbers in parenthesis are t-statistics. * *and* ** *indicate statistical significance at the 5% and 1% level, respectively. Regression periods are 1987-2019, 2000-2019, and 2005-2019 for BTOP, SGTR, and HFRM, respectively.*

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