Trading Strategy Research – Time Series Momentum

Group 3

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Introduction

Momentum trading strategies are usually implemented as cross-sectional trading strategies among individual stocks, but rather than focus on the relative returns of securities in the cross-section, we decide to focus on TSMOM. Time series momentum is the performance of a price series compared to its past performance. While some people still think an asset's recent return cannot be used to predict future returns, they do not pay much attention to this strategy. However, a study from Moskowitz shows that this investment strategy is worth studying.

The rest of the paper is organized as follows. Section 2 describes the purpose and motivation of this paper. Section 3 provides literature review and more detail between cross-sectional and time series momentum. Section 4 describes our data. Section 5 describes our assumptions and model. Section 6 examines TSMOM and buy & hold strategy by adding backtest and Momentum performance analysis on them. Section 7 is the conclusion.

Purpose and motivation

Moskowitz et al. (2012) show that the trend-pricing anomaly exists across time and asset classes. They documented the effect in equity indexes, currency, commodity, and bond futures for a 25 years data set. They find that each instrument's past 12-month excess return is a positive predictor of its future return. This time series momentum or "trend" effect persists for about a year and then partially reverses over longer horizons.

Why is TSMOM important for the derivative trading market? The answer is that it can give speculators a better way to get profit. Speculators can trade with time series momentum to take advantage of the positive return trend for the first 12 months and reduce their positions when the trend reverses. As a result, speculators can profit from time series momentum at the expense of hedgers.

Besides, Moskowitz also claimed that the profit of time series momentum seems to reach a maximum during severe stock market volatility. If this is true, time series momentum may be a good hedge against extreme events.

Since the research done by Moskowitz et al. was in 2012, it has been a long time. We decided to check the efficiency of TSMOM using data more recently. Also compare this to buy and hold strategy to see which one has better performance. Additionally, we can use our data set to check whether the return of TSMOM tends to be large when the stock market's returns are most extreme.

A literature survey

Traditional cross-sectional momentum is a popular and very well-documented anomaly. Traditional momentum uses a universe of assets to pick past winners, and it predicts that those winners will continue to outperform their peers in the future as well. However, recent academic research shows that we do not need the whole universe of assets to exploit the momentum effect. A new version of this anomaly (Time Series Momentum) shows that each security's (or asset's) own past return is a future predictor. The past 12-month excess return of each instrument is a positive predictor of its future return. A diversified portfolio of time-series momentum across all assets is remarkably stable and robust, yielding a high Sharpe ratio with little correlation to passive benchmarks. An additional advantage is that time-series momentum returns appear to be largest when the stock market's returns are most extreme; hence, time-series momentum may be a hedge for extreme events. So we focus on this data (TSMOM) for the strategy using purchased futures data from Pinnacle Data Corp CLC Database.

We also use the background of Cross-Sectional and Time-Series Determinants of Momentum Returns which was published by Narasimhan Jegadeesh, Sheridan Titman. Portfolio strategies that buy stocks with high returns over the previous 3–12 months and sell stocks with low returns over this same time period perform well over the following 12 months. A recent article by Conrad and Kaul (1998) presents striking evidence suggesting that the momentum profits are attributable to cross-sectional differences in expected returns rather than to any time-series dependence in returns. This article shows that Conrad and Kaul reach this conclusion because they do not take into account the small sample biases in their tests and bootstrap experiments. Our unbiased empirical tests indicate that cross-sectional differences in expected returns explain very little, if any, of the momentum profits.

Also from Time series momentum which published by Tobias J.Moskowitz ,YaoHuaOoi , LasseHejePedersen, we could know that time-series momentum returns appear to be largest when the stock market's returns are most extreme; hence, time-series momentum may be a hedge for extreme events.

Data

To backtest the time series momentum strategy and report the performance, we used the future data from Pinnacle Data Crop CLC Database. We only use a part of the original data and the part we used contains the complete data of 48 contracts from 1990 to 2020, which was also used by Lim et al (2019) to introduce deep momentum networks based trading rules into the volatility scaling framework of time-series momentum.

To process the raw data which contains 98 contracts traded across FX, Fixed Income, Commodities and Equity, we did some preformatting including a backwards ratio-adjusted method to obtain the continuous price series. Here are some visualizations of the pre-processed data.

In [9]:
```
data_set[0].head()
```

Out[9]:

Asset	Date	Open	High	Low	Settle	Volume	Open_Interest	Short_Rate_Daily	Short_Rate_Annual	Returns_Daily	Next_Returns_Daily	...	MACD_16_48	MACD_32_96	Binary_N
AN	1990-01-02	43.46	43.51	43.30	43.30	125	2576	0.000325	0.0854	-0.007564	-0.003695	...	1.396906	1.486063	
	1990-01-03	43.23	43.31	43.12	43.14	1495	3232	0.000319	0.0837	-0.003695	0.009736	...	1.305883	1.473971	
	1990-01-04	43.33	43.63	43.29	43.56	932	3145	0.000316	0.0829	0.009736	-0.006428	...	1.298588	1.478928	
	1990-01-05	43.32	43.45	43.28	43.28	272	2567	0.000313	0.0820	-0.006428	0.002773	...	1.238528	1.472797	
	1990-01-08	43.45	43.46	43.34	43.40	177	2456	0.000315	0.0827	0.002773	0.001152	...	1.205557	1.471873	

5 rows × 27 columns

In [10]:
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data_set[0].tail()
```

Out[10]:

Asset	Date	Open	High	Low	Settle	Volume	Open_Interest	Short_Rate_Daily	Short_Rate_Annual	Returns_Daily	Next_Returns_Daily	...	MACD_16_48	MACD_32_96	E
ZZ	1994-12-23	254.618	256.083	252.013	253.478	8790	32877	0.000205	0.0531	-0.002562	0.001925	...	0.165366	-1.388443	
	1994-12-27	252.013	254.455	250.548	253.966	3164	33298	0.000216	0.0560	0.001925	0.014746	...	0.285656	-1.325528	
	1994-12-28	253.641	257.874	253.641	257.711	5570	33042	0.000212	0.0548	0.014746	-0.002526	...	0.429000	-1.246148	
	1994-12-29	256.897	258.687	254.618	257.060	7657	34350	0.000212	0.0549	-0.002526	-0.003167	...	0.542132	-1.174323	
	1994-12-30	258.525	260.153	254.618	256.246	8202	36217	0.000191	0.0494	-0.003167	-0.002544	...	0.627223	-1.110317	

5 rows × 27 columns

Assumptions

The trend-pricing anomaly exists across time and asset classes.

Moskowitz et al. (2012) demonstrated this claim, reporting strong persistence in returns during 1-12 month lags as well as evidence of mean reversion over longer time horizons. They also showed that cross-sectional momentum is closely related to the TSMOM factor. According to Moskowitz et al. (2012), a R^2 of 44% exists between an all-asset TSMOM component and the all-asset cross-sectional factor produced by Asness et al. (2010), indicating that the two factors capture a large portion of each other's variance.

The price series of each asset in our data are continuous.

Contract expiration periods range from monthly to quarterly, depending on the underlying asset. To fully assess the profitability of trading strategies using historical futures contract data, these contracts must be combined into a continuous price series. In order to get a continuous price series for each asset, some preformatting is required due to the fact that the raw data consists of a series of distinct maturity futures contracts. Because the ratio-adjusted method does not cause a jump in the continuous price series, which is a trait that we want to have if we are going to be working with return data.

Then we decompose each futures contract's past return into the change in the underlying spot asset's price and the return that is related to the shape of the futures curve.

$$Future\ return\ =\ Price\ change -\ roll\ return$$

Momentum

Cross-Sectional Momentum:

Momentum profits are barely explained by cross-sectional differences in expected returns.

While cross-sectional variation in expected returns could theoretically explain the observed momentum profits, Jegadeesh et al. (2002) concluded that its contribution in practice is likely to be very small. Intuitively, this is because the cross-sectional variation in unconditional expected returns is small relative to the variation in realized returns, and a stock's realized returns over any six-month period provide little information about the stock's unconditional expected returns. Thus, the unconditional expected returns of past winners are unlikely to differ significantly from those of past losers. Their empirical tests support this intuition.

Time-Series Momentum:

The dominant force for both cross-sectional and time-series strategies is the significant positive auto-covariance between a security's next-month excess return and its lagged 1-year return.

Time-series momentum exhibits strong and consistent performance across many different asset classes, is lightly loaded with standard risk factors, and performs well during extreme periods, all of which challenge random walk hypothesis and standard rational pricing models.

The link between time-series momentum returns and the positions of speculators and hedgers suggests that speculators profit from time-series momentum at the expense of hedgers.

Strategy & Methodology

Buy-and- hold

Buy and hold is a long-term passive investment strategy in which investors maintain a generally constant portfolio over time, despite short-term fluctuations.

On average, buy and hold investors outperform active management over longer time horizons and after expenses, and they can often delay capital gains taxes. However, some critics believe that buy-and-hold investors may fail to sell at appropriate moments. Some buy-and-hold investors neglect to implement simple risk management strategies. Investors who completely ignore price when making buy or sell decisions are susceptible to the risk of buying high and selling low. And this strategy has no way to profit from market volatility.

TSMOM

We employ the TSMOM method proposed by Moskowitz et al. as a TSMOM factor (2012). The following formula describes the strategy:

$$r_{t,t+1}^{TSMOM} = SIGN(r_{t-12,t}^{s})\frac{\sigma_{tgt}}{\sigma_t^s}r_{t,t+1}^{s}$$

$$SIGN(x) = \begin{cases} 1 & \text{if } x > 0 \\ -1 & \text{otherwise} \end{cases}$$

Where s denotes the traded asset or contract, t denotes the time frame, and σ_t is a backward-looking volatility estimator for asset s, where σ_{tgt} represents the target volatility. This trading technique, or rule, entails buying an asset if it has had a net positive return over the previous 12 months and selling it if not.

By mathematically integrating the risk-weighted returns and leveraging it to a desired target volatility, we can produce a cross-asset TSMOM portfolio.

To achieve this, add up all of assets s :

$$r_{t,t+1}^{TSMOM} = \frac{1}{N}\sum_{s=1}^{N} SIGN(r_{t-12,t}^{s})\frac{\sigma_{tgt}}{\sigma_t^s}r_{t,t+1}^{s}$$

N is the total number of assets. This strategy is effective at capturing TSMOM.

Factors

The benchmarks used for the factor analysis are:

- SMB - Size

- HML - Value vs growth
- MOM - Cross sectional Momentum
- BOND - Barclay's Aggregate Bond Index
- EQUITY - MSCI World equity index
- COMMODITY - S&P GSCI Index

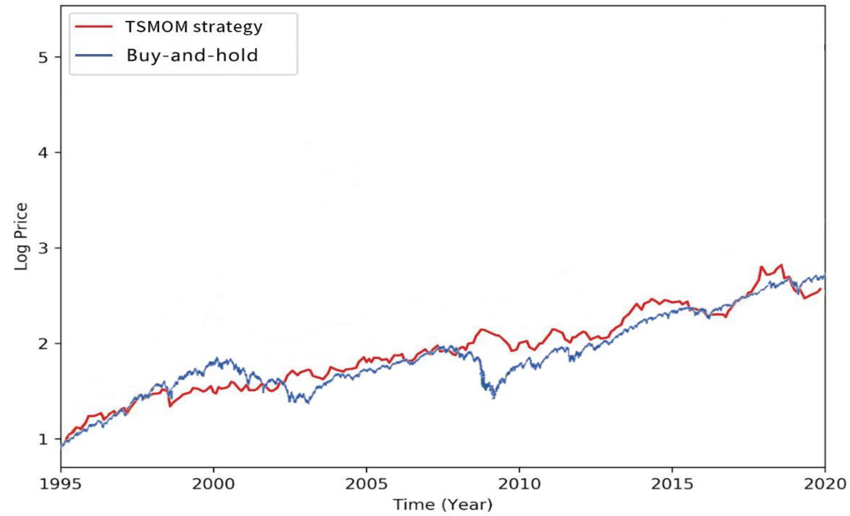
Backtest

Backtesting is the process of comparing the accuracy of a strategy or forecast model to past data. It can be used to test and compare the viability of trading methods, allowing traders to implement and fine-tune winning tactics. The results of the backtest are shown below.

	ZM	US	ZK	ZN	TY	FB	PA	CN	FN	ZL	...	JO	ZZ	SN	
E[Return]	-0.029446	0.032393	0.005625	0.001491	0.058048	0.081569	0.089354	0.013919	0.009755	0.019316	...	-0.033105	-0.011515	-0.006027	-0.0143
E[Excess Return]	-0.030420	0.007723	0.003067	0.004292	0.027579	0.044254	0.086318	0.012458	0.010767	0.025193	...	-0.030839	-0.015059	0.006055	-0.0089
Std[Return]	0.160812	0.156675	0.159206	0.163685	0.156898	0.157434	0.163859	0.159096	0.155955	0.156953	...	0.165644	0.157110	0.168953	0.1615
Skew[Return]	-0.189931	-0.174434	-0.170542	-0.047738	-0.102333	-0.071406	0.158683	-0.209126	-0.120720	-0.215206	...	-1.503853	0.020845	-4.372202	-0.2782
Exc.Kurtosis[Return]	3.359337	1.112800	3.001134	4.362220	1.585089	2.104369	6.772640	2.199634	1.408356	1.694972	...	42.786704	0.755653	137.648129	4.3847
Sharpe	-0.189163	0.049294	0.019267	0.026224	0.175774	0.281098	0.526779	0.078304	0.069042	0.160514	...	-0.186173	-0.095848	0.035836	-0.0553
Max_Drawdown	-0.812272	-0.521493	-0.570428	-0.646750	-0.527391	-0.453876	-0.474444	-0.477487	-0.660232	-0.488473	...	-0.748043	-0.711706	-0.660577	-0.5958
Max_Drawdown_Duration (Years)	10.130952	8.192000	14.980159	24.345238	8.192000	5.692000	7.198413	8.604743	11.706349	6.730159	...	28.365079	21.023810	15.023715	26.7698

8 rows × 48 columns

We display the performance of the TSMOM and the buy-and-hold strategy. We observe that TSMOM produces smaller downturns than the buy and hold strategy.



Then we do a quantitative evaluation of the two strategies. For comparison, strategies were both normalized for a target vol of 15%. The Table below shows the relevant performance.

	BUY-AND-HOLD	**TSMOM**
E[RETURN]	0.063597	0.098382
E[EXCESS RETURN]	0.033735	0.075886
STD[RETURN]	0.178116	0.163695
SKEW[RETURN]	0.045155	-0.621192
EXC.KURTOSIS[RETURN]	11.292540	5.796160
SHARP	0.1893997	0.463580
MAX_DRAWDOWN	-0.628860	-0.298306
MAX_DRAWDOWN_DURATION (YEAR)	13.297619	3.507937

The Sharp ratio compares the return of an investment with its risk. The greater a portfolio's Sharpe ratio, the better its risk-adjusted performance. A negative Sharpe ratio means the risk-free or benchmark rate is greater than the portfolio's historical or projected return, or else the portfolio's return is expected to be negative. Note that the TSMOM has better expected return and the Sharp ratio of the TSMOM strategy is 25 percent higher than that of the buy-and-hold strategy. That means TSMOM has better risk-adjusted performance. But the Sharpe ratio of the TSMOM is also below 1. Therefore, we can say that the TSMOM is sub-optimal, and there is a lot of scope for improvement. In addition, we can see that TSMOM does very well on maximum drawdown, which over 25 years of observation was 30%. This indicates that TSMOM has smaller losses than buy-and-hold strategy.

Momentum Performance Analysis

OLS Regression Results

Dep. Variable:	PORTFOLIO	R-squared:	0.032
Model:	OLS	Adj. R-squared:	0.017
Method:	Least Squares	F-statistic:	2.153
Date:	Fri, 18 Nov 2022	Prob (F-statistic):	0.0469
Time:	07:47:49	Log-Likelihood:	816.70
No. Observations:	393	AIC:	-1619.
Df Residuals:	386	BIC:	-1592.
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0111	0.002	6.510	0.000	0.008	0.014
SMB	0.0018	0.002	0.787	0.432	-0.003	0.006
HML	0.0043	0.003	1.342	0.180	-0.002	0.011
MOM	0.0054	0.003	2.079	0.038	0.000	0.011
BOND	0.1535	0.130	1.182	0.238	-0.102	0.409
EQUITY	-0.0797	0.037	-2.137	0.033	-0.153	-0.006
COMMODITY	-0.0138	0.028	-0.485	0.628	-0.070	0.042

Omnibus:	9.812	Durbin-Watson:	1.870
Prob(Omnibus):	0.007	Jarque-Bera (JB):	17.506
Skew:	0.046	Prob(JB):	0.000158
Kurtosis:	4.030	Cond. No.	86.4

By using the OLS regression method to do the factor analysis, the p-value is 0.04 which is nearly 0 which could imply that this equation is significant. TSMOM is negatively correlated with the EQUITY (MSCI World equity index) and COMMODITY (S&P GSCI Index). However, the p value for COMMODITY is 0.628 which is high thus it is not significant. Also, one must be cautious with the adjusted R-squared is only 0.02.

Conclusion

Therefore, by looking at the period from 1990 to 2020, there is a significant time series momentum effect over the period 1990-2020. And this effect exists across time and asset classes. In the backtest part, it concludes that the performance of TSMOM has been quite impressive with the Sharpe ratio at 0.46 for 1990-2020 which is better than buy and hold strategy. The result indicates that TSMOM delivers higher profits during the most extreme market movements and it also concurs Moskowitz, T. J., Ooi, Y. H., & Pedersen's findings. Thus, time series momentum is still relevant for today's market and provides a viable strategy for speculators to gain profits.

However, the TSMOM's Sharpe ratio is less than 1. As a result, we may conclude that the TSMOM is not at its best and has much potential for improvement.

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The contribution of each team member

Yi Xu: Introduction, Proposal and motivation, Code for TSMOM

Dong An: Literature survey, Code for TSMOM

Yunneng Qian: Data, Models, Momentum performance analysis

Yuqi Wang: Strategy and Methodology, Assumption, Backtest

Qixuan Zheng: Backtest, Momentum performance analysis, Conclusion