Trend following strategy in futures using Time Series Momentum (TSMOM) and Continuous forecasts (CF)

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https://github.com/jironghuang/trend_following

0. Executive summary

Before June 2010, across different configurations, trend following strategies perform well with sharpe of > 1, high calmar ratio, reasonable drawdowns.

After June 2010, risk adjusted returns, sharpe ratio dropped off signficantly with peformance dropping to below 0.7 for both strategies.

Despite the deterioration in performance of trend following strategies, it may still have a place in an investor's portfolio. According to Kathryn Kaminski, chief investment strategist at AlphaSimplex group and Visiting Lecturer in Finance at the MIT Sloan School of Management mentioned that trend following exhibits a crisis alpha characteristic. She studied 800 years of crises and found that all crises create trends and there are opportunities for divergent strategies.

1. Project motivation

As David Ricardo, a British economist in the 19th century once said, 'cut short your losses and let your profits trend' allude to the point that trend following as a profitable strategy could exist even back then.

Having read AQR's papers on the Time Series Momentum (TSMOM, I am keen to explore this topic in the futures space (Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012)). Besides AQR papers, I have also followed closely the work of Robert Carver, an ex-MAN AHL quant who specialized in the space of intermediate to long term trend-following futures strategies.

In this study, I will be exploring 2 approaches,

i.) TSMOM approach developed by AQR
ii.) Continuous forecasts approach (loosely based on Robert Carver's framework in his books Leveraged Trading and Systematic Trading)

**Note: But because of limitations of the dataset that I will be using, I'm unable to incorporate 'carry roll returns forecasts' in Robert Carver's books. I believe this would have impact on the effectiveness of the strategy.*

The performance of strategies will be evaluated across 2 periods,

i.) In-sample period: 1984 to June 2010
ii.) Out-of-sample period: June 2010 to 2016

2. Dataset

For this study, I will be using Futures dataset across 4 asset classes: Indices, Bonds, Currencies, Commodites provided by Quantopian up till 2016. The continuous dataset is presumably stiched through backward, forward or proportional adjusted methodology (not explicitly mentioned in Quantopian’s github repository).

Below is the descriptive statistics on 50 instruments used in this study.

		Start	Mean	Std	Skew	Kurt	Sharpe Ratio
ASSET_CLASS	**FUTURES**						
	AUSTRALIA 10-YEAR BOND	1987-09-22	-0.0169	0.0129	-0.3327	4.4011	-1.3127
	AUSTRALIA 3-YEAR BOND	1989-12-04	-0.0125	0.0127	-0.1874	4.2914	-0.9784
	CANADA 10-YEAR BOND	1989-09-19	0.02	0.0619	-0.1983	2.077	0.323
	EURO BOBL	1991-10-08	0.0095	0.0328	-0.2232	2.0057	0.2901
	EURO BUND	1990-11-27	0.0218	0.0542	-0.1682	1.7197	0.4021
	EURO BUXL	1998-10-06	0.05	0.1111	-0.1073	2.28	0.4504
	EURO SCHATZ	1997-03-11	-0.0059	0.0129	-0.3343	4.828	-0.4558
	JAPAN 10-YEAR BOND	1985-10-22	0.01	0.0491	-0.7532	11.7342	0.204
	LONG GILT	1984-01-03	0.0056	0.0734	0.0973	3.5171	0.0766
	US 10-YEAR NOTE	1984-01-03	0.0194	0.0657	0.0494	3.1977	0.2959
	US 2-YEAR NOTE	1990-06-27	-0.0042	0.0164	-0.1006	5.3188	-0.2532
	US 5-YEAR NOTE	1988-05-24	0.0062	0.0405	-0.0993	2.8186	0.1539
BOND	**US LONG BOND**	1984-01-03	0.0323	0.1033	-0.0517	1.7271	0.3127
	ALUMINIUM	1997-07-25	-0.0228	0.2091	-0.1205	2.2338	-0.1091
	BRENT CRUDE	1988-06-27	0.1343	0.3427	-0.2832	10.6529	0.3918
	COCOA	1984-01-03	-0.0187	0.2912	0.1385	2.694	-0.0643
	COFFEE	1984-01-03	-0.0349	0.3614	0.5525	8.6241	-0.0964
	COPPER	1997-07-23	0.0953	0.2624	0.0753	4.4137	0.3632
	COTTON	1984-01-03	0.0045	0.2532	0.1114	2.3473	0.0177
	GASOIL	1989-07-05	0.094	0.3159	-0.2581	10.5074	0.2976
	GOLD	1984-01-03	-0.0079	0.1635	-0.0206	7.2019	-0.0485
	HEATING OIL	1986-07-02	0.1259	0.3481	-0.2403	9.2525	0.3618
	LEAN HOGS	1986-04-03	0.0002	0.2288	-0.0767	1.2639	0.0008
	LIVE CATTLE	1984-01-03	0.0164	0.1449	-0.0825	1.2337	0.113
	NATURAL GAS	1990-04-05	-0.036	0.505	0.4978	5.322	-0.0713
	NICKEL	1997-07-25	0.1186	0.3632	0.0631	3.4288	0.3266
	PLATINUM	1984-01-30	0.0278	0.2281	-0.29	8.3065	0.1217
	RBOB GASOLINE	2005-10-05	0.131	0.3691	0.0252	2.88	0.3549
	SILVER	1984-01-03	0.0017	0.2876	-0.4577	6.1662	0.0061
	SOYMEAL	1984-01-03	0.0927	0.2468	0.0353	2.302	0.3756
	SOY OIL	1984-01-03	-0.0268	0.2314	0.2112	1.7495	-0.1159
	SUGAR	1984-01-03	0.0344	0.3584	-0.0553	3.8837	0.0959
	WTI CRUDE	1984-01-03	0.1119	0.3667	-0.2354	9.9236	0.3052
COMMODITIES	**ZINC**	1997-07-25	0.0333	0.2924	-0.0614	3.2482	0.114
	AUSTRALIAN DOLLAR	1987-01-14	0.0135	0.1187	-0.504	8.9221	0.1135
	CANADIAN DOLLAR	1986-04-07	-0.0099	0.0755	-0.0001	6.2528	-0.1307
	EURO	1998-05-21	-0.0132	0.0994	0.005	1.3993	-0.1326
	JAPANESE YEN	1986-05-28	-0.0267	0.1105	0.573	6.8125	-0.2413
	NEW ZEALAND	1997-05-09	0.0253	0.1339	-0.2431	3.1446	0.1892
	NORWAY	2002-05-20	0.0128	0.1274	-0.2333	2.4129	0.1002
	SWEDEN	2002-05-20	0.0036	0.1255	0.1515	4.5578	0.0283
	SWITZERLAND	1986-04-08	-0.0068	0.1198	1.4176	36.1815	-0.0572
CURRENCIES	**UK**	1986-05-29	-0.0068	0.0987	-0.4535	6.2524	-0.0689
	AEX (NETHERLANDS)	1989-01-04	0.0377	0.2335	-6.3787	230.991	0.1613
	DAX (GERMANY)	1990-11-27	0.0744	0.2273	-0.0274	5.539	0.3275
	FTSE/MIB (ITALY)	2004-03-24	0.0222	0.2437	-0.1146	5.4227	0.091
	IBEX 35 (SPAIN)	1992-07-02	0.0906	0.2395	-0.0977	5.3238	0.3781
	S&P 500 (US)	1997-09-11	0.0464	0.1991	0.0991	10.2515	0.2331
	SPI 200 (AUSTRALIA)	2000-05-04	0.0333	0.1619	-0.2786	4.6234	0.2059
EQUITY INDEXES	**TOPIX (JAPAN)**	1990-05-21	-0.005	0.2369	0.0742	8.5367	-0.0211

3. TSMOM methodology

In AQR papers, the authors experimented with fixed lookback periods of 1 year which determines the trading signal for the next month i.e. if price of an asset increase over 1 year period, the trading signal for next month would be long. Reverse holds when price of an asset decreased. Position of each asset is based on lookback exponential standard deviation of daily returns with annualized volatility of 40%.

The following is the explanation by the authors,

> *...Since volatility varies dramatically across our assets, we scale the returns by their volatilities in order to make meaningful comparisons across assets. We estimate each instrument's ex ante volatility σ_t at each point in time using an extremely simple model: the exponential weighted lagged squared daily returns (i.e., similar to a simple univatiate GARCH model). Specifically, the ex ante annualized variance σ_t^2 for each instrument is calculated as follows:*
>
> $$\sigma_t^2 = 261\sum_{i=0}^{\infty}(1-\delta)\delta^i(r_{t-1-i}-\bar{r}_t)^2$$
>
> *where the scalar 261 scales the variance to be annual, the weights $(1-\delta)\delta^i$ add up to one, and $\bar{r}_t$ is the exponentially weighted average return computed similarly. The parameter δ is chosen so that the center of mass of the weights is $\sum_{i=0}^{\infty}(1-\delta)\delta^i i = \delta/(1-\delta) = 60$ days. The volatility model is the same for all assets at all times...*

Capital is distributed amongst instruments with available data. For example, if there are only X instruments before 1987, the portfolio returns will be the average of returns from X instruments.

4. Continuous forecasts methodology

In conventional technical analysis, trade entries and exits are usually binary in nature, and current position size is dependent on entry and exit conditions defined t periods ago.

Current position size ~ Entry, exit conditions (dependent on current state) defined t periods ago

But in the financial world, asset returns outcome are continuous in nature with a distribution. Hence it would be optimal for current position size to be directly proportionate to Expected Returns conditional on current forecast, risk capital allocation, current volatility of instrument, overall portfolio volatility, correlation matrix, cost of rebalancing. This reasonates with the Bayesian school of thought in which probability of hypothesis should be updated as more evidence becomes available.

Current position size ~ E(Returns | current forecast, risk capital, current volatility of instrument, overall portfolio volatility, correlation matrix, cost of rebalancing)

The advantage of continuous forecasts approach is that you only need to compare optimal position size given current conditions against current positions. If it diverges by x%, then you rebalance. The risk management layer and position sizing is inherently built into the framework. And it is not dependent on the state of current position. This is different from a binary trading system which is state dependent.

4.1 Computation of raw continuous forecasts

For the purpose of my study, I will be considering 2 commonly used technical indicators,

- Exponential moving averages
- Donchian channels

4.1.1. Exponential moving averages

1) Selection of pairs of fast and slow moving averages to reflect different time-frames: **8-32, 16-64, 32-128, 64-254**
2) Raw forecast: First, I take the difference between pair of moving averages
3) Risk-adjusted forecast: Next, I divide raw forecast by instrument-risk (volatility of instrument in price unit) to get a risk adjusted forecast.

```
def raw_ewmac(price, Lfast=8, Lslow=None):
    """
    Calculate the ewmac trading rule forecast, given a price and EWMA speeds Lfast, Lslow and vol_lookback
    """
    if Lslow is None:
        Lslow=4*Lfast

    fast_ewma=price.ewm(span=Lfast).mean()
    slow_ewma=price.ewm(span=Lslow).mean()
    raw_ewmac=fast_ewma - slow_ewma

    vol=robust_vol_calc(price.diff()).to_frame()

    forecast = raw_ewmac.to_frame()/ np.array(vol)

    return forecast
```

4.1.2. Donchian Channels

1) Selection of lookbacks to reflect different time-frames: 40, 80, 160, 320
2) Forecast: Derived by taking difference between current price with middle price (half of max and min over N lookback) divided by difference max and minimum price over N lookback. The formula is as follows, $40 * (P_{t} - R_{middle\ N}) / (R_{maxN} - R_{minN})$. 40 multiplier is applied to scale forecasts up to a range of (-20, 20)

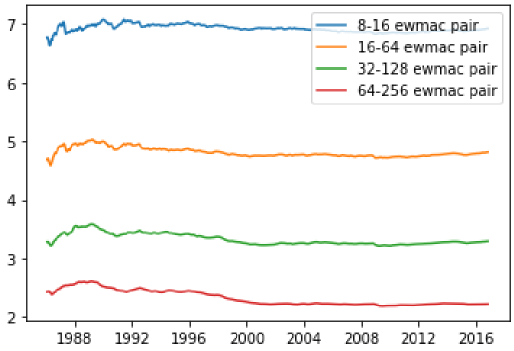
```
def raw_breakout(price, lookback, smooth = None):

    roll_max = price.rolling(lookback).max()
    roll_min = price.rolling(lookback).min()
    roll_mean = (roll_max + roll_min) / 2

    forecast = 40 * ( price - roll_mean ) / (roll_max - roll_min)

    return forecast
```

4.1.3. Forecast scalar: Rescaling forecasts to average value of 10 for consistency across instruments and time

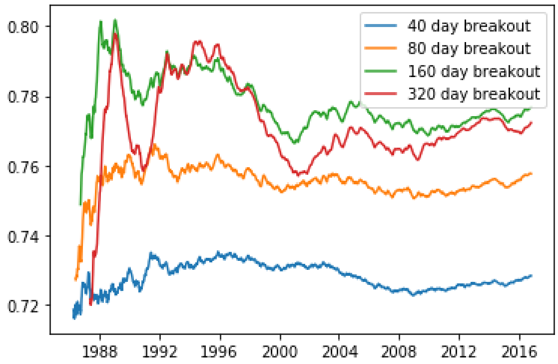
1) Absolute median forecasts across instruments within a forecast type (e.g 8-32 exponential moving average forecast) is extracted for each day.
2) Next, an expanding window is used to compute the average value of median forecasts in point
3) Then, I compute the forecast scalar by dividing average value in point 2 with 10 i.e. we scale the forecast to an average absolute value of 10. 10 represents the average forecast strength for each instrument. In the graphs below, you will notice that forecast scalar plateaus to a level as time progresses (i.e. because of averaging effect over larger data points).

Forecast scalar i.e. multiplier with raw forecasts to scale average forecasts to avg absolute value of 10

EWMAC forecast scalar



Breakout forecast scalar



4) Lastly, the forecast scalar is mapped against the instruments' individual forecasts time series. Adjusted forecasts are capped between a range of [-20, 20]. This is to avoid overly optimistic or pessemistic forecasts resulting in outsize position of any particular instrument in the portfolio.

```
def compute_forecast_scalar(xcross, target_abs_forecast=10,window=250000,min_periods=500,backfill=True):

    if xcross.shape[1] == 1:
        x = xcross.abs().iloc[:, 0]
    else:
        x = xcross.ffill().abs().median(axis=1)

    avg_abs_value = x.rolling(window=window, min_periods=min_periods).mean()
    scaling_factor = target_abs_forecast / avg_abs_value

    return scaling_factor
```

```
def compute_norm_forecast(norm_price, forecast_mtd=raw_ewmac, param=8):

    raw_forecast = [forecast_mtd(norm_price[i],param) for i in norm_price]
    raw_forecast = pd.concat(raw_forecast, axis=1)
    forecast_scalar = compute_forecast_scalar(raw_forecast)
    adj_forecast = raw_forecast.multiply(forecast_scalar, axis="index")

    adj_forecast_cap = adj_forecast.copy()
    adj_forecast_cap[adj_forecast_cap > 20] = 20
    adj_forecast_cap[adj_forecast_cap < -20] = -20

    return raw_forecast, forecast_scalar, adj_forecast, adj_forecast_cap
```

4.1.4. Combining adjusted forecasts into weighted forecast for each instrument

From section 4.1.3, I would obtain adjusted forecasts for each instrument. The next step is to combine the forecasts via weights. In this study, I will be using 2 weighting schemes,

1.) Equal weight

In the first weighting scheme, I assign equal weights to the rules. In my study, I have 8 different forecasts, 4 for exponential moving averages and 4 for Donchian Channels. 12.5% weight is allocated to each of these forecasts.

2.) Weighting through block bootstrapping

In the next weighting scheme, I performed the following steps,

i. Within the in-sample period, I extract 25 blocks of continuous daily periods. Each period accounts for 25% of available days.
ii. For each instrument, I compute the returns stream, $_{AR_{it}}$ associated with each forecasts. First, similar to TSMOM, I find the leverage, L_{it} required to bring up the realized volatility, Vol_{it-1} to a reference level of 40%. Next, I scale the leverage up/down according to the strength of the forecasts.

$$AR_{it} = 40\%/Vol_{it-1} * F_{it} * R_{it} = L_{it} * F_{it} * R_{it}$$

iii. Commission costs of 0.1% is also imposed per trade to penalize frequent rebalancing. Rebalancing only occurs when current forecasts differs from last forecasts by X points (In optimization, found to be 6 points at the overall level).
iv. With the derived returns stream, I proceed to find optimal weights, W_{rbi} amongst rules, r for the highest sharpe associated for each boostrapped block, b per instrument, i.
v. Lastly, I pooled the weights together and find the average optimal weights across instruments for in-sample period,

$$W_{r\,=}\ Average_{bi}\,(W_{rbi})$$

ewmac8	0.111069
ewmac16	0.041851
ewmac32	0.063619
ewmac64	0.200274
breakout40	0.281200
breakout80	0.111628
breakout160	0.081539
breakout320	0.108819

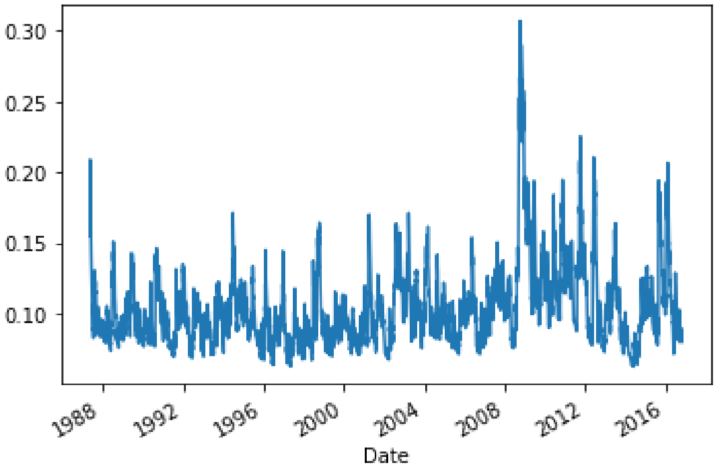
Note: Applying optimized weights for each instrument is avoided because of relative small number of boostrapped blocks. And based on Robert Carver's advice, instruments are more likely to be similar than different in their momentum characteristic. That being said, in my next iteration, I could test this hypothesis.

4.1.5. Scaling up or down at portfolio level according to maximum overall portfolio risk allowed

With diversification across the instruments and forecasts, the realized volatility of the portfolio would be significantly lower than the reference annualized volatility of 40% per instrument. In AQR's study, the annualized volatility averaged around 12%.

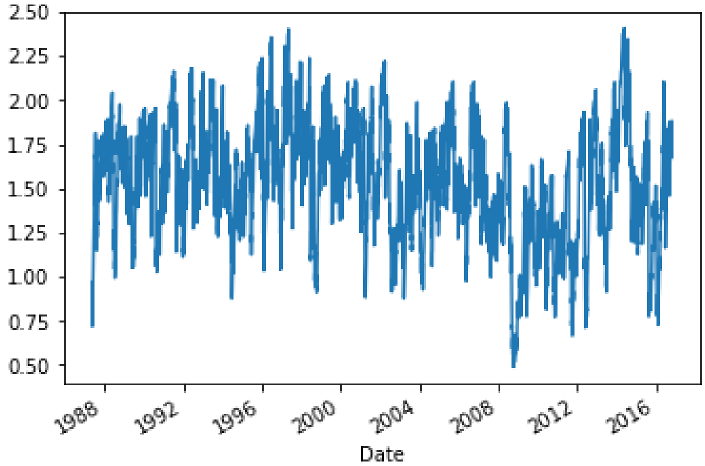
For the purpose of this study, I will use a maximum realized volatility cap at 15%. The steps are as follow,

i. Assume forecasts, F_{t-1} are at both extreme of -20 and +20 depending on the polarity of the forecasts. And find the maximum realized volatility, Mv_{t-1}



ii. Next, find the leverage adjustment factor, A_t at the portfolio level,

$$A_t = \text{Maximum realized volatility cap of } 15\% / Mv_{t-1}$$



** Note that during 2008-2009 crisis, adjustment factor to portfolio dived to 0.50, suggesting that correlation across instruments could have increased.*

iii. Last but not the least, I will map the leverage adjustment factor, A_t to the leverage factor in section 4.1.4 (2ii). The final leverage, FL_{it} for the instrument will be as follows,

$$FL_{it} = A_t * L_{it}$$

iv. In terms of position sizing, let's say if instrument is assigned a risk capital of \$20,000. The notional capital, NC_{it} to be deployed for this instrument would be

$$NC_{it} = FL_{it} * \$20{,}000$$

Note: An alternative is to consider the correlation matrix between instruments and find the adjustment factor.

4. Evaluation of strategies

I tested the following strategies on in-sample (before 2010-06-07) and out-of-sample periods (after 2010-06-06). Below are the different configurations,

i. TSMOM excluding costs in sample: AQR TSMOM strategy is tested on in sample period excluding costs.

ii. TSMOM including costs in sample: AQR TSMOM strategy is tested on in sample period including costs.
iii. Pre-optimize in sample: Equal weights are allocated to different forecasts. And the strategy is tested on in sample period.
iv. Optimize in sample: Optimized weights based on block boostrapping are allocated to different forecasts. And the strategy is tested on in sample period.
v. Pre-optimize out of sample: Equal weights are allocated to different forecasts. And the strategy is tested on out of sample period.
vi. Optimize out of sample: Optimized weights based on block boostrapping are allocated to different forecasts. And the strategy is tested on out of sample period.

4.1 Summary statistics on monthly returns

Performance during in sample period

Across the board, during the in-sample period, I notice that both types strategies perform well with sharpe of > 1, high calmar ratio, reasonable drawdowns for both TSMOM and continuous forecasts methodology.

Surprisingly, TSMOM 1 year lookback methodology performs better than the continuous forecasts despite the diversification of signals and risk management at the portfolio level.

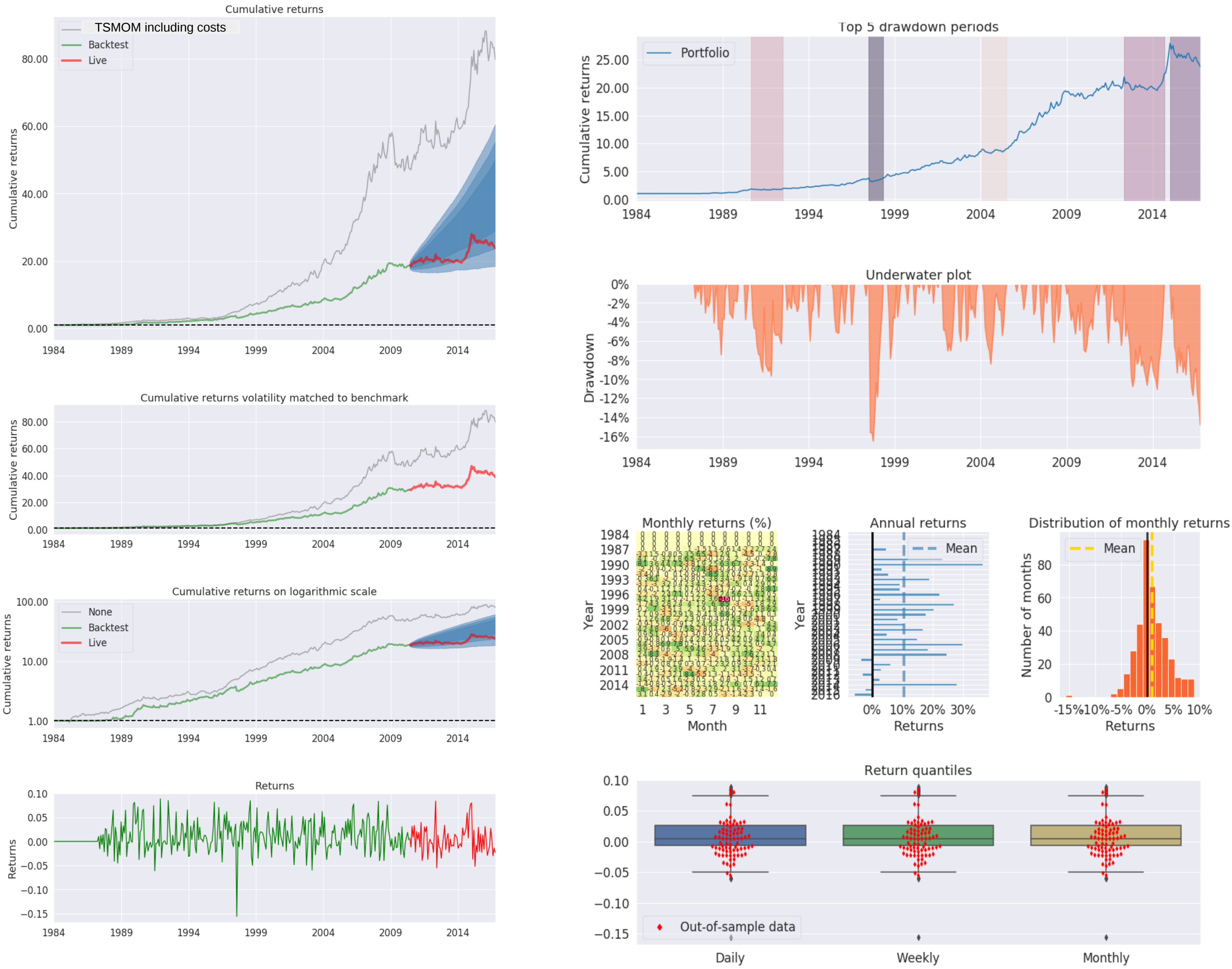
Performance during out of sample period

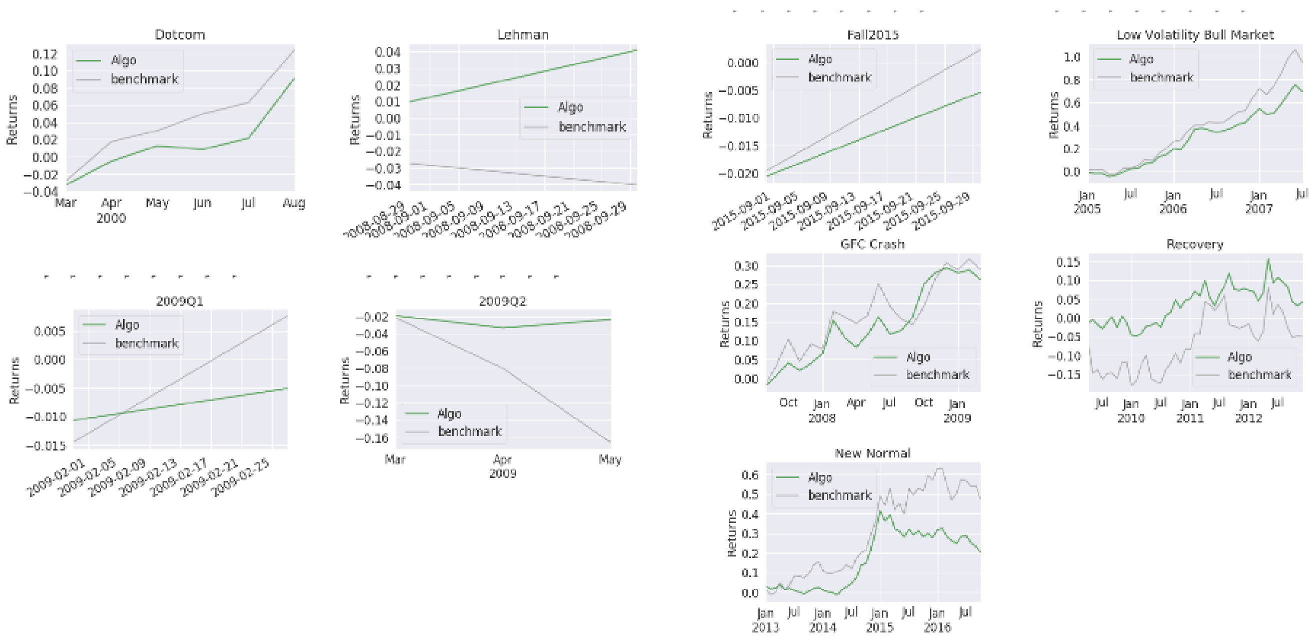
During the out-of sample period, risk adjusted returns, sharpe ratio dropped off signficantly with peformance dropping to below 0.7 for both strategies. TSMOM strategy still performs better than continuous forecasts.

According to David Harding, founder of Winton Group and pioneer of quantitative trend following mentioned in an article that one reason for the deterioration in returns could be the overcrowdedness and commoditization of the strategy.

strategy	sharpe	annualized_returns	annualized_sd	max_drawdown	calmar_ratio
TSMOM excluding costs in sample	1.45	0.18	0.12	-0.19	0.96
TSMOM including costs in sample	1.35	0.17	0.12	-0.20	0.85
Pre_optimize_insample	1.11	0.12	0.11	-0.14	0.85
Optimize_insample	1.12	0.12	0.10	-0.17	0.71
Optimize_outsample	0.46	0.04	0.10	-0.13	0.32
Pre_Optimize_outsample	0.48	0.05	0.11	-0.14	0.33
TSMOM including costs_out_sample	0.67	0.08	0.13	-0.13	0.63

4.2 Equity curves of both methodologies





4.3 Factor analysis against Fama French 3 factors, Momentum factor, Bonds and Commodity returns

TSMOM in sample data

Factor analysis showed that only Bond and Market(Equity) factors are significant. And TSMOM exhibit a negative beta for Market (Equity) factor and huge beta for Bond factor. This seems to bode well for a crisis-alpha based strategy as Equities tend to dive during a crisis.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       strategy_returns   R-squared:                       0.035
Model:                            OLS   Adj. R-squared:                  0.020
Method:                 Least Squares   F-statistic:                     2.342
Date:                Wed, 23 Dec 2020   Prob (F-statistic):             0.0311
Time:                        13:11:20   Log-Likelihood:                 759.33
No. Observations:                 392   AIC:                            -1505.
Df Residuals:                     385   BIC:                            -1477.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0117      0.002      5.982      0.000       0.008       0.016
SMB           -0.0002      0.003     -0.085      0.932      -0.005       0.005
HML           -0.0007      0.004     -0.182      0.855      -0.008       0.007
MOM            0.0054      0.003      1.802      0.072      -0.000       0.011
BOND           0.3005      0.150      2.004      0.046       0.006       0.595
EQUITY        -0.0974      0.043     -2.268      0.024      -0.182      -0.013
COMMODITY     -0.0288      0.033     -0.880      0.379      -0.093       0.036
==============================================================================
Omnibus:                        0.439   Durbin-Watson:                   1.938
Prob(Omnibus):                  0.803   Jarque-Bera (JB):                0.263
Skew:                           0.034   Prob(JB):                        0.877
Kurtosis:                       3.107   Cond. No.                         86.6
==============================================================================
```

Boostrap optimized in sample

Similar to TSMOM, the strategy exhibits a negative beta for Market (Equity) factor. This also bodes well for a crisis-alpha based strategy as Equities tend to dive during a crisis.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       strategy_returns   R-squared:                       0.036
Model:                            OLS   Adj. R-squared:                  0.017
Method:                 Least Squares   F-statistic:                     1.931
Date:                Wed, 23 Dec 2020   Prob (F-statistic):             0.0754
Time:                        13:17:42   Log-Likelihood:                 669.78
No. Observations:                 318   AIC:                            -1326.
Df Residuals:                     311   BIC:                            -1299.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0105      0.002      5.618      0.000       0.007       0.014
SMB           -0.0008      0.002     -0.321      0.749      -0.005       0.004
HML            0.0028      0.003      0.836      0.404      -0.004       0.009
MOM            0.0003      0.003      0.094      0.925      -0.006       0.006
BOND          -0.0969      0.133     -0.732      0.465      -0.358       0.164
EQUITY        -0.1022      0.039     -2.606      0.010      -0.179      -0.025
COMMODITY      0.0582      0.031      1.887      0.060      -0.002       0.119
==============================================================================
Omnibus:                       34.429   Durbin-Watson:                   2.049
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              166.930
Skew:                          -0.214   Prob(JB):                     5.64e-37
Kurtosis:                       6.524   Cond. No.                         82.5
==============================================================================

Warnings:
```

TSMOM out of sample

Results mirrors in sample data.

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:       strategy_returns   R-squared:                       0.035
Model:                            OLS   Adj. R-squared:                  0.020
Method:                 Least Squares   F-statistic:                     2.342
Date:                Wed, 23 Dec 2020   Prob (F-statistic):             0.0311
Time:                        13:40:59   Log-Likelihood:                 759.33
No. Observations:                 392   AIC:                            -1505.
Df Residuals:                     385   BIC:                            -1477.
Df Model:                           6                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0117      0.002      5.982      0.000       0.008       0.016
SMB           -0.0002      0.003     -0.085      0.932      -0.005       0.005
HML           -0.0007      0.004     -0.182      0.855      -0.008       0.007
MOM            0.0054      0.003      1.802      0.072      -0.000       0.011
BOND           0.3005      0.150      2.004      0.046       0.006       0.595
EQUITY        -0.0974      0.043     -2.268      0.024      -0.182      -0.013
COMMODITY     -0.0288      0.033     -0.880      0.379      -0.093       0.036
==============================================================================
Omnibus:                        0.439   Durbin-Watson:                   1.938
Prob(Omnibus):                  0.803   Jarque-Bera (JB):                0.263
Skew:                           0.034   Prob(JB):                        0.877
Kurtosis:                       3.107   Cond. No.                         86.6
==============================================================================
```

Boostrap optimized out of sample

Results do not mirror in sample data. Negative market beta relationship is not present in out of sample data.

Moreover it exhibits positive significant relationship with Bonds and negative significant relationship with commodity.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       strategy_returns   R-squared:                       0.328
Model:                            OLS   Adj. R-squared:                  0.270
Method:                 Least Squares   F-statistic:                     5.617
Date:                Wed, 23 Dec 2020   Prob (F-statistic):           8.60e-05
Time:                        13:21:17   Log-Likelihood:                 178.82
No. Observations:                  76   AIC:                            -343.6
Df Residuals:                      69   BIC:                            -327.3
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0003      0.003      0.088      0.930      -0.006       0.007
SMB           -0.0090      0.006     -1.568      0.121      -0.021       0.002
HML            0.0103      0.008      1.303      0.197      -0.005       0.026
MOM            0.0014      0.004      0.330      0.743      -0.007       0.010
BOND           0.8559      0.364      2.350      0.022       0.129       1.583
EQUITY         0.0351      0.094      0.373      0.710      -0.152       0.222
COMMODITY     -0.2427      0.063     -3.839      0.000      -0.369      -0.117
==============================================================================
Omnibus:                        0.759   Durbin-Watson:                   1.938
Prob(Omnibus):                  0.684   Jarque-Bera (JB):                0.345
Skew:                           0.137   Prob(JB):                        0.842
Kurtosis:                       3.184   Cond. No.                         133.
==============================================================================
```

Conclusion

Despite the deterioration in performance of trend following strategies, it still has a place in an investor's portfolio. According to Kathryn Kaminski, chief investment strategist at AlphaSimplex group and Visiting Lecturer in Finance at the MIT Sloan School of Management mentioned that trend following exhibits a crisis alpha characteristic. She studied 800 years of crisis and found that all crises create trends and there are opportunities for divergent strategies.

Future developments for the strategy

- In the next iteration, I am keen to explore the feasibility of the strategy beyond 2016 data
- At the moment, the data used in this study is stiched together by Quantopian (extracted from Bloomberg). In the next iteration, I am keen to stitch the contracts together either through the forward or backward adjustment method. With the individual contracts, I am also able to incorporate carry term structure (contango or backwardation) signal into the continuous forecasting system
- The block bootsrapped optimization may not have worked well because I only extracted 25 continuous periods from the dataset. Ideally I would prefer to extract significantly more blocks of data (~1000) but I am constrained by the computing power. In the next iteration, I would explore using cloud platforms (e.g. Google Collaboratory or AWS) for bootstrap optimization
- In the next iteration with more computing power, I would perform a boostrap optimization and walk forward analysis. That is to say, I derive optimize weights from t-x to t and test the results on t+1. This will be repeated in each time step with an expanding window.

Disclaimer

Author has no postion in this study's strategy but has keen interests in developing and investing in a viable trend following strategy across across asset classes.

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