Conference on
Financial Mathematics and
Engineering

Uncovering Momentum with Intertemporal Analysis

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Takeaways

- The momentum premium represents a long-term ongoing puzzle and challenge to the Efficient Market Hypothesis pursued by multiple theories.
- The recently developed open-source fsharadar module added the keystone extension to the Zipline-based platform for running diverse financial economics studies.
- Divide-and-conquer approach steered the direction of momentum studies towards the performance of top decile winners during the bull market.
- Rolling intertemporal analysis brings a transparent approach for exploring the momentum effect across the different levels.
- The momentum effect can be explicitly explained for 2011-2019 as the sampling of high volatility growth stocks.

Outline of the Talk

- Quest towards the Source of the Momentum Premium
- Overview of Integrated Research Platform
- Extracting Momentum Effect with Divide-and-Conquer Approach
- Explaining Momentum Effect with Intertemporal Analysis
- Concluding Remarks

QUEST TOWARDS THE SOURCE OF THE MOMENTUM PREMIUM

Momentum Everywhere

Definition of strategy: ranking stocks by prior performance and going long past winners while shorting past losers.

Selected publications (in chronological order) accessing and demonstrating the momentum premium across a broad range of dimensions including asset classes, markets, and time horizons:

1993: Momentum Effect - N. Jegadeesh and S. Titman

1997: 4 Factor Model - M.M. Carhart

2012: Time Series Momentum - T.J. Moskowitz, Y.H. Ooi, and L.H. Pedersen

2013: Value and Momentum Everywhere - C. Asness, T. Moskowitz, L. Pedersen

2013: MSCI USA Momentum Index

2014: Fact, Fiction, and Momentum Investing - C. Asness et al.

2016: Two Centuries of Price Return Momentum - C. Geczy and M. Samonov

2017: A Century of Evidence on Trend-Following Investing - B.K. Hurst, Y.H. Ooi, L.H. Pedersen

2019: Factor Momentum Everywhere - T. Gupta and B. Kelly

EMH Challenge and Pursued Theories

The existence and universality of the momentum premium represents an ongoing challenge for risk based models and the Efficient Market Hypothesis. Subsequently, this triggered a number of behavioral models for explaining this phenomenon (Subrahmanyam, 2018):

- Models based on psychological biases: conservatism and representativeness (Barberis et al., 1998); overconfidence and self-attribution (Daniel et al., 1998)
- Multi-agent models: interaction between heterogenous agents, newswatcher and momentum traders (Hong and Stein, 1999)
- Models based on disposition effect: tendency of investors to sell stocks increasing in value too soon while holding on to stocks decreasing in value for too long that led to unrealized capital gains driving out returns (Grinblatt and Han, 2005)
- Frog-in-the-Pan Hypothesis: investor underreaction to information that comes in continuously and in small amounts (Da et al., 2014)

Characteristic-Specific Analysis

Moving down to the stock level connects the analysis to studies on momentum returns and firm characteristics that in general are related with behavioral models and can be interpreted as a proxy for information uncertainty.

- Size: firm equity market value (Jegadeesh and Titman, 1993)
- R^2 of regression on market returns: (Hou et al., 2006)
- Turnover: 12 month average of # monthly shares traded / # shares outstanding (Lee and Swaminathan, 2000)
- Age: number of years that have passed since the IPO date (Zhang, 2006)
- Analyst coverage: number of I/B/E/S earning estimates (Hong et al., 2000)
- Forecast dispersion: standard deviation of earnings per share forecast / mean (Zhang, 2006)
- Book-to-market ratio: (Daniel and Titman, 1999)
- Illiquidity: 52 week average of absolute value of weekly log returns / weekly trading volume (Amihud, 2002)
- Credit rating: (Avramov et al., 2007)

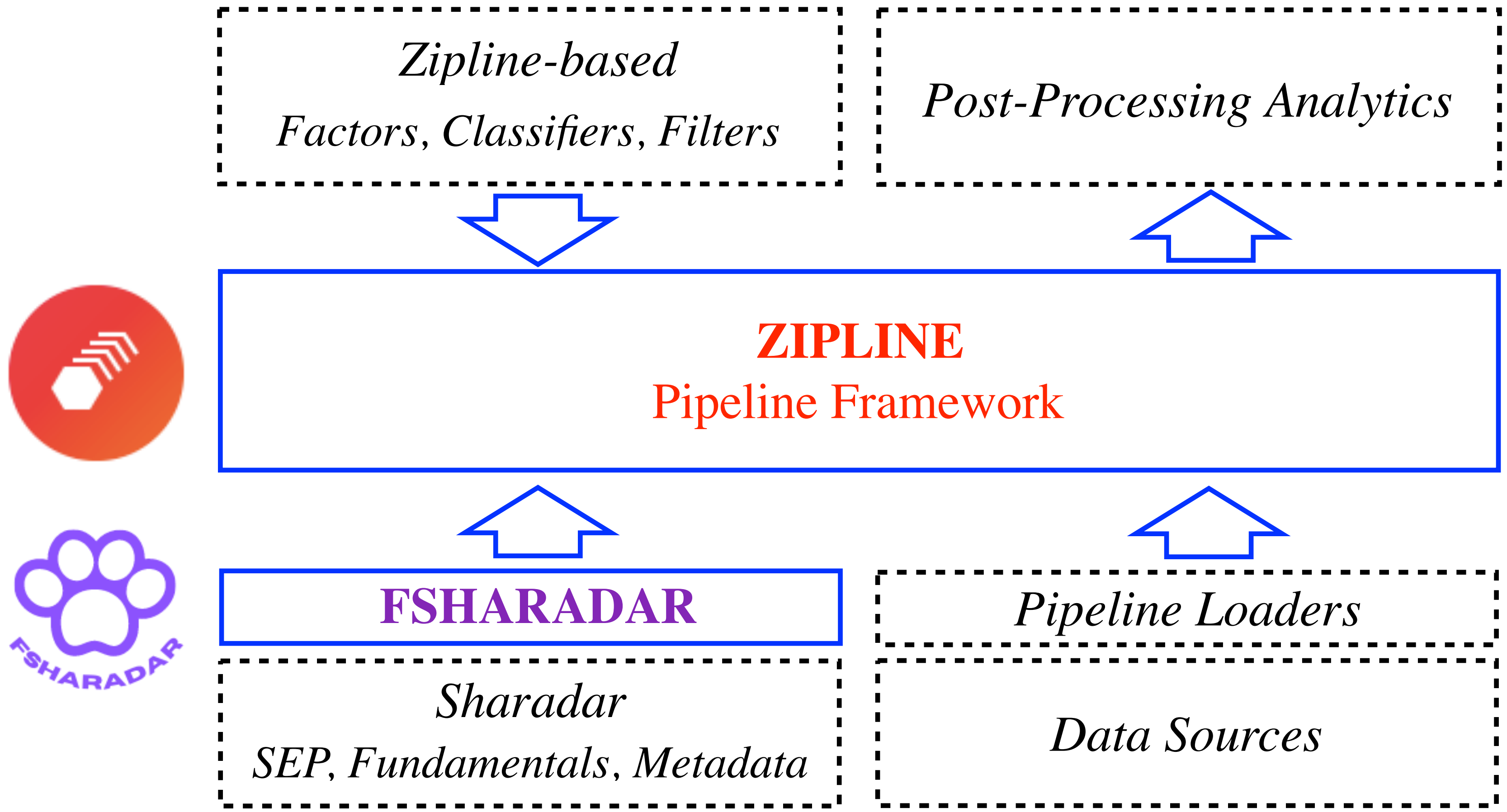
Bandarchuk and Hilscher (2011) however showed that characteristic screens increase momentum profits due to more extreme sort of past returns.

Müller and Müller (2019) conducted a study with 18 stock characteristics and across 14 countries. Their results though demonstrated the relation of characteristics to momentum profits even after controlling the interrelations with extreme past returns.

INTEGRATED RESEARCH PLATFORM

Integrated Research Platform

The Zipline-based research platform is built around the Pipeline framework enabling to connect multiple data sources with multiple analytical approaches for conducting diverse backtest studies. The figure provides a conceptual outline of its architecture.



Within this framework, the Pipeline is a custom collection of cross-sectional trailing-window tasks (Factors, Classifiers, and Filters) propagated by Pipeline Engine through the backtest interval. From the user perspective, the task can be implemented as a specialization of the CustomFactor class.

The Zipline data layer is organized as a collection of named data bundles associated with different data sets. The FSharadar extension implements two bundles produced from Sharadar Equity Prices (SEP) and Daily Metrics of Core US Fundamental Data.

Defining Pipeline Components - 1 of 2

The Zipline pipeline framework is designed as an optimal set of base classes (such as Pipeline Engine, Pipeline Loader, Factor, Pipeline) that can be independently extended for producing an open collection of custom applications. Then, the building pipeline represents a sequence of steps for selecting and connecting together appropriate pipeline components.

Pipeline Loaders

The first step is associated with the selection of data bundles and initialization of Pipeline Loaders. The current version of the fsharadar module supports two bundles that can be accessed independently and used together for analysis of factor anomalies. Furthermore, this set of bundles can be extended with additional data sources for addressing the new questions raised by the study.

```
sep_bundle_data = sep.load()
daily_bundle_data = daily.load()

sep_pipe_loader = sep.PipelineLoader(sep_bundle_data)
daily_pipe_loader = daily.PipelineLoader(daily_bundle_data)
```

Pipeline Engine

Even the single Pipeline task may require multiple characteristics. The code snippet below shows how the configuration of the Pipeline Engine combines Pipeline Loaders selected in the previous step.

```
def get_pipe_loader(column):
    if column in USEquityPricing.columns:
        return sep_pipe_loader
    if column in daily.Fundamentals.columns:
        return daily_pipe_loader
    raise ValueError("No PipelineLoader registered for column %s." % column)

engine = SimplePipelineEngine(
    get_loader=get_pipe_loader,
    asset_finder=sep_bundle_data.asset_finder)
```

Defining Pipeline Components - 2 of 2

Pipeline Universe

The pipeline universe defines a subset of stocks that meet a set of criteria. Designed after the popular Quantopian version, the *fsharadar* module provides the built-in TradableStocksUS universe that selects domestic common stocks with market cap bigger than $350 million, median daily dollar volume greater than or equal to 2.5 million over the trailing 200 days, and closing price higher than $5 per share.

```
from fsharadar.universe import TradableStocksUS
universe = TradableStocksUS()
```

Pipeline Custom Factors

Finally, the pipeline task represents the computation of stock characteristics within the trailing windows. While some computations are implemented as Zipline built-in factors, the collection of common factors can be further extended by specializing the CustomFactor class. The code snippet below shows the implementation of the conventional momentum factor computing their prior behavior over the course of 11 months with a 1 month lag.

```
wl = 252
class Momentum(CustomFactor):
    """ Conventional Momentum factor """
    inputs = [USEquityPricing.close]
    window_length = wl

    def compute(self, today, assets, out, prices):
        out[:] = (prices[-21] - prices[-wl])/prices[-wl]
```

Building and Running Pipeline

Application-related built-in and custom computations can be combined together within a single Pipeline. The code snippet below shows the example used in Uncovering Momentum studies.

```
def make_pipeline():
    pipe = Pipeline()
    pipe.add(Momentum(mask=universe), "mom")
    pipe.add(RealizedVolatility(mask=universe), "rv")
    pipe.add(Latest([daily.Fundamentals.marketcap], mask=universe), "cap")
    pipe.add(bp.quartiles(mask=universe), "bp_quartile")
    pipe.set_screen(universe)
    return pipe

pipe = make_pipeline()
```

Pipeline is run within the pipeline engine by calling the corresponding method and specifying timestamps of start_date and end_date:

```
pipe_df = engine.run_pipeline(pipe, start_date, end_date)
```

The method returns the two-index (date-asset) dataframe with columns corresponding to pipeline entries.

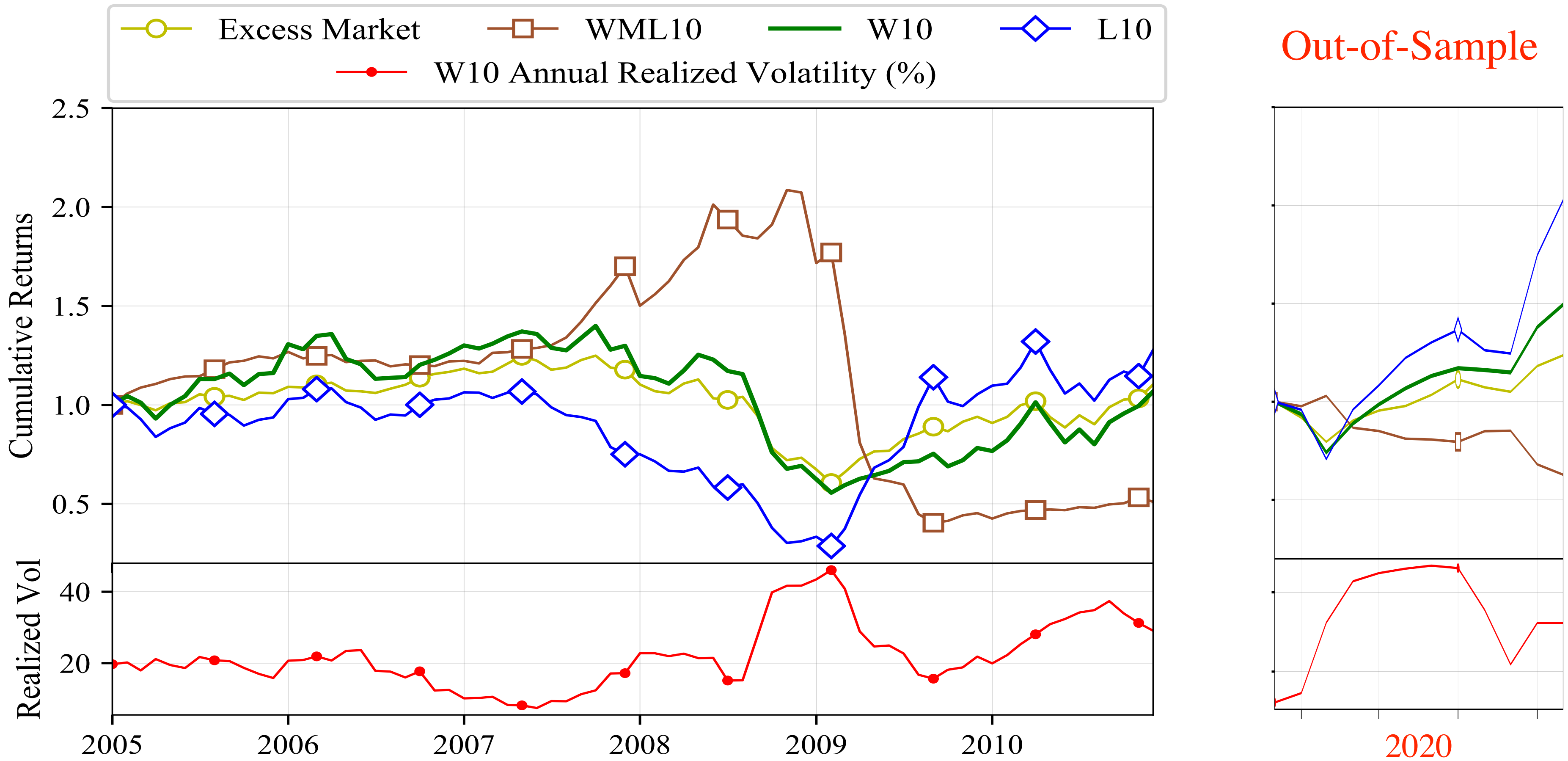
EXTRACTING MOMENTUM EFFECT WITH DIVIDE-AND-CONQUER APPROACH

Momentum Behavior During Market Crashes

The figures below show the broken momentum behavior during bear markets where the past winners and losers portfolios switch places.

The left figure spans the 2005-2010 interval with the 2008 market downturn covered by Daniel and Moskowitz (2016). A subsequent study extended the analysis in connection to the volatility timed winners approach (Malitskaia, 2019a).

The right figure shows the 'out-of-sample' performance during the 2020 crash and confirms the previous results.



Source: K.R. French Data Library, https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

★ The documented broken behavior triggered new questions rooted in the theory behind momentum, and prompted to apply a detailed multi-step divide-and-conquer approach (Malitskaia, 2019b) beginning with dissecting the momentum analysis along two dimensions: bull/bear market states and winners/loser deciles.

Four Heterogenous Cases

Reported are the α and β parameters for the momentum deciles presented separately for the bull and bear states across the January 1927 to December 2020 interval. The bull market is defined by the cumulative two year past returns with nonnegative values as computed by Daniel and Moskowitz (2016).

	P1	P2	P3	...	P8	P9	P10
Bull Market							
alpha	II. -11.27	-4.35	-2.43	...	2.11	2.42	I. 4.35
	(-6.35)	(3.48)	(-2.36)	...	(2.96)	(2.94)	(-3.50)
beta	1.31	1.07	0.96	...	0.99	1.07	1.27
	(38.25)	(44.28)	(28.27)	...	(72.13)	(67.34)	(52.75)
Bear Market							
alpha	III. -0.49	2.87	3.25	...	1.39	1.72	IV. 2.96
	(-0.10)	(0.82)	(0.94)	...	(0.90)	(0.92)	(1.06)
beta	1.83	1.60	1.38	...	0.87	0.86	0.80
	(34.66)	(43.70)	(49.89)	...	(54.45)	(44.16)	(27.53)

Source: K.R. French Data Library, https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

I. Winners represent the solo driver producing annual mean with positive alpha and beta greater than one during bull states.
II. Losers in the bull state in contrast generate a small annual mean as a byproduct of the difference between a negative alpha and beta of the winners level.
III. Loser's alpha becomes zero and beta is increased.
IV. The alpha and beta parameters of past winners are substantially reduced.

★This heterogeneous behavior suggests that each decile/market case requires independent evaluation and the most unblemished case is represented by the winners performance in the bull market state.

Extracting Common Effect Across Strategies - 1 of 2

A momentum decile return $r_t^{MOM,P}$ can be defined with a portfolio equation where stocks are selected based on rank of the prior returns P=$rank(r^s{}_{t,prior})$ and weighted with one of the conventional schemes:

$$r_t^{MOM,P} = \sum_{s \in P} w_t^s \cdot r_t^s, \text{ where } w_t^s \equiv \text{ equal or value weights}$$

Time series momentum (TSMOM) (Moskowitz et al., 2012) represents an alternative strategy that selects assets based on sign of the prior returns and multiplies weights with a volatility scaling component:

$$r_t^{TSMOM} = \sum_{s=1}^{S_t} w_t^s sign(r_{t,prior}^s) r_t^s \text{ , where } w_t^s = \frac{1}{S_t} \cdot \frac{40\%}{\sigma_t^s}$$

As presented in "Momentum and Volatility Timing" at SIAM'19, the volatility scaling of TSMOM enhanced the performance of the strategy during bear markets. Subsequently, the volatility-timed winners approach replaced scaling with a threshold function for bypassing the market downturns.

From the perspective of this Uncovering Momentum study, the threshold function explicitly separates scaling from momentum effects and creates a common basis for analyzing alternative momentum strategies. Then the unscaled TSMOM positive and negative portfolios can be decomposed via momentum deciles:

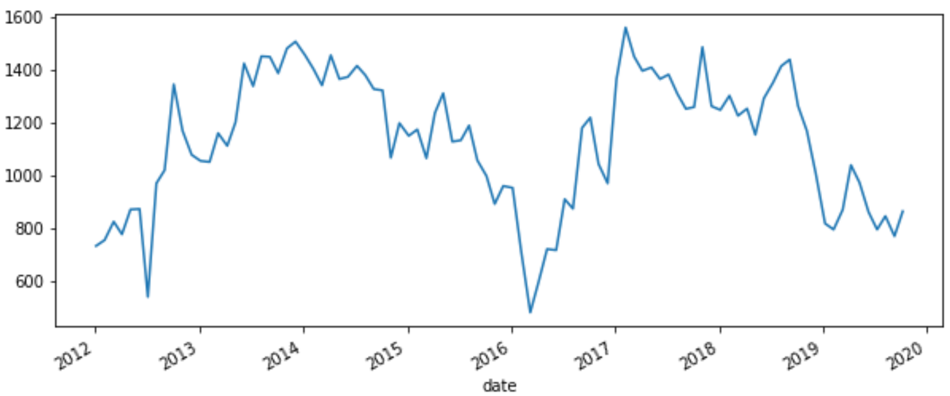
★ $$r^{TSMOM,pos/neg} \sim \sum_{Top/Bottom} w_t^{P,pos/neg} \cdot r_t^{MOM,P}$$

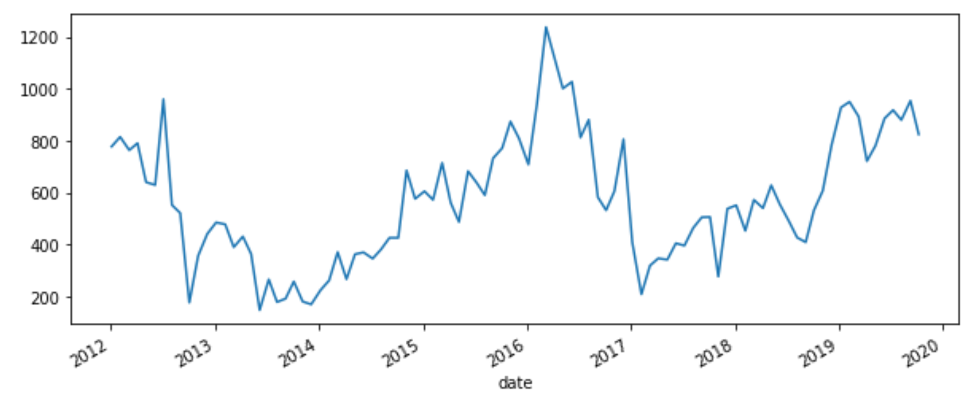
Extracting Common Effect Across Strategies - 2 of 2

Postitive TSMOM

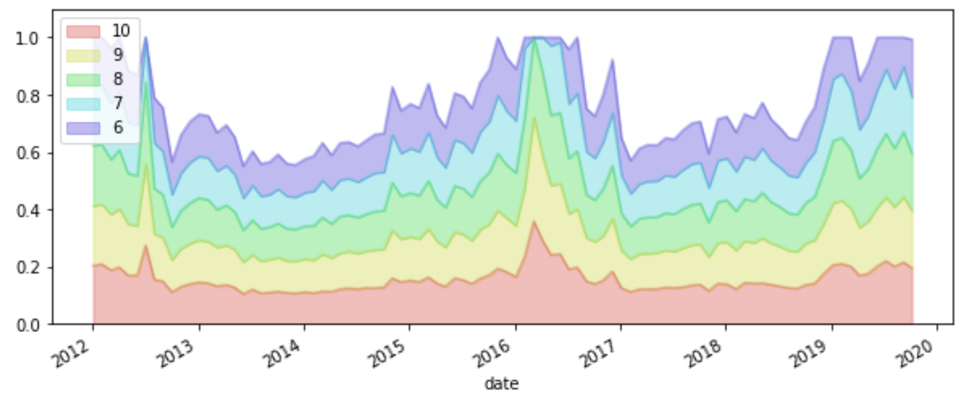
Negative TSMOM

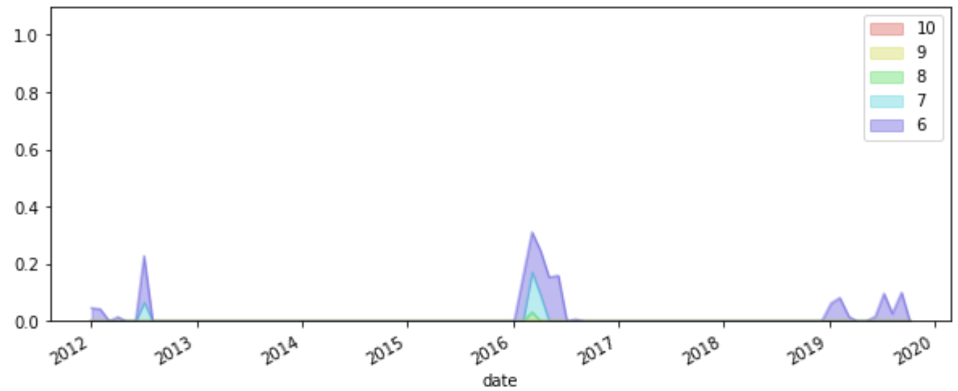
Counts



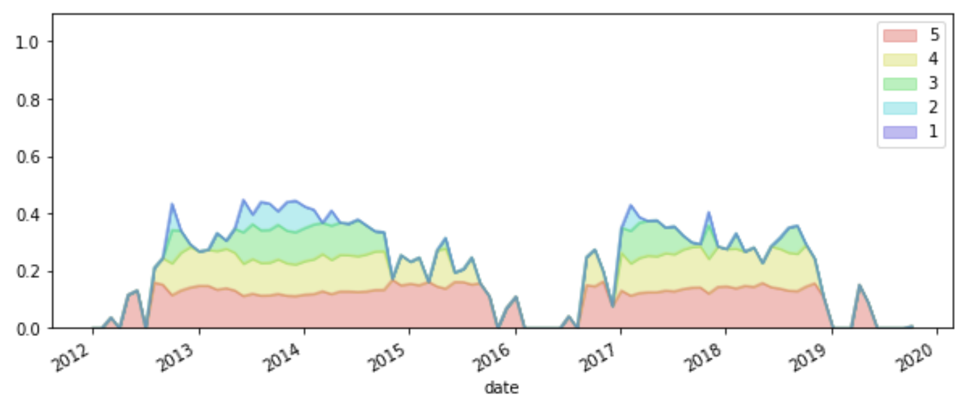


Top
Momentum
Decile





Bottom
Momentum
Decile



EXPLAINING MOMENTUM EFFECT WITH INTERTEMPORAL ANALYSIS

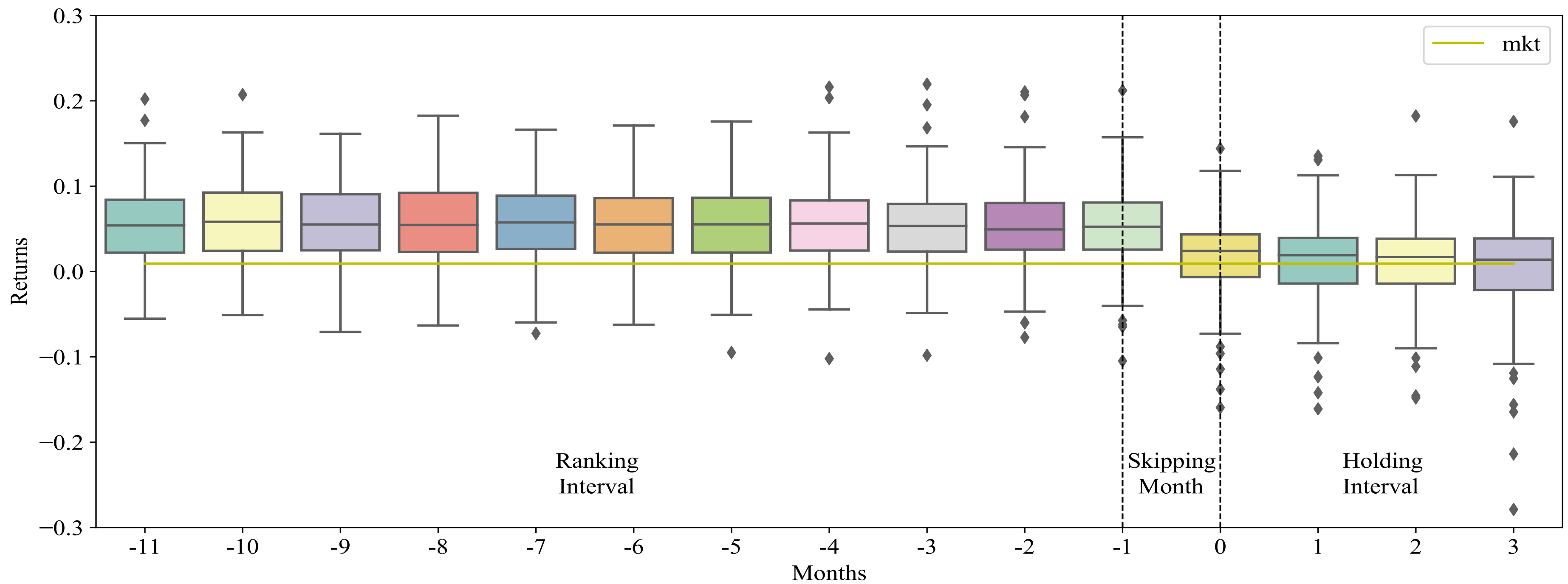
Rolling Intertemporal Analysis

This research explores the momentum effect from the data-driven direction with the rolling intertemporal analysis integrating the intertemporal event study approach (Fama et al., 1969) and the rolling analysis technique (DeMiguel et al., 2009). Similar to an event study, the portfolio formation date constitutes the event and analysis conducted across the ranking and holding intervals. Analogous with rolling window forecasting, the ranking period is associated with the in-sample interval.

The approach is implemented in the following steps:

- It begins with creating a pipeline to calculate the prior returns across all stocks in the TradableStocksUS universe for a 12-month ranking period lagged one month.
- Then, stocks are ranked based on their priors.
- Next, the selected deciles are rolled forward. Simultaneously, value-weighted portfolios with one-month returns are collected for each month during the combined in-sample and out-of-sample intervals relative to the momentum formation date.

The figure presents the boxplot results for the top deciles summarizing the monthly distributions of portfolio returns over the in- and out-of-samples.



Random Sampling Model of Ranking Interval

Model

The left ranking part of the figure prior to the bump can be explained by a random sampling model based on a set of permutations with repetitions $(x^i_1, \ldots, x^i_T)$ where x^i_t represents a random rank within [1,10] for the t-th month within the ranking interval T.

After aggregating the ranks over interval T, the permutations can be subsequently sorted for selecting and computing the average rank of the top decile P10:

$$\text{Average Rank}^{Model,P10} = \frac{1}{N_{P10}} \sum_{P10} \left(\frac{1}{T} \sum_{T} x^i_t \right)$$

Actual Data

The momentum average rank aggregated across the ranking interval T and time horizon M can be calculated as:

$$\text{Average Rank}^{MOM,P10} = \frac{1}{T} \sum_{T} \left(\frac{1}{M} \sum_{m} x^{MOM,P10}_{m,t} \right)$$

where x are monthly (m) time series of value-weighted decile portfolios with return ranks for calculating the t-th month in ranking interval T:

$$x^{MOM,P10}_{m,t} = \frac{1}{N_{P10}} \sum_{P10} w^s_t \cdot rank(r^s_{t,prior})$$

The Table below presents the comparison of AverageRanks of the top decile P10 between the momentum (MOM) data and model.

conventional strategy

Ranking Intervals, T	1	2	3	4	5	6	7	8	9	10	11
MOM	10.00	8.66	8.12	7.78	7.54	7.37	7.26	7.17	7.08	7.01	6.94
Model	10.00	9.00	8.35	7.94	7.66	7.45	7.29	7.17	7.06	6.97	6.89

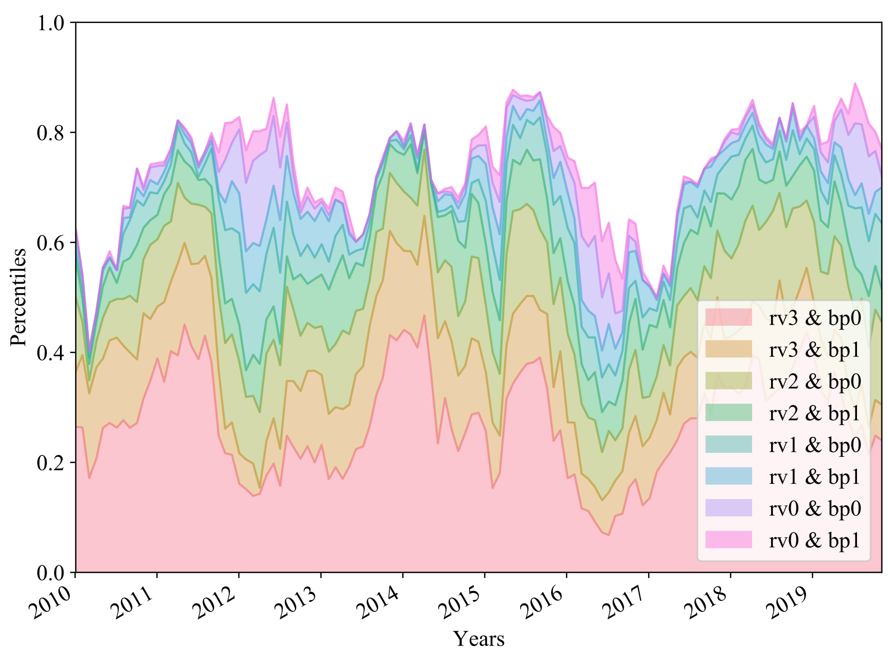
★ As shown in the Table, both the momentum data and model display similar results for each ranking interval T from 1 to 11 months. Following this model, the rank after the one month skipping interval should be approximately 5.5. The out-of-sample momentum however exhibits a non-zero premium and hence defines a criterion for assessing the underlying momentum theories and models.

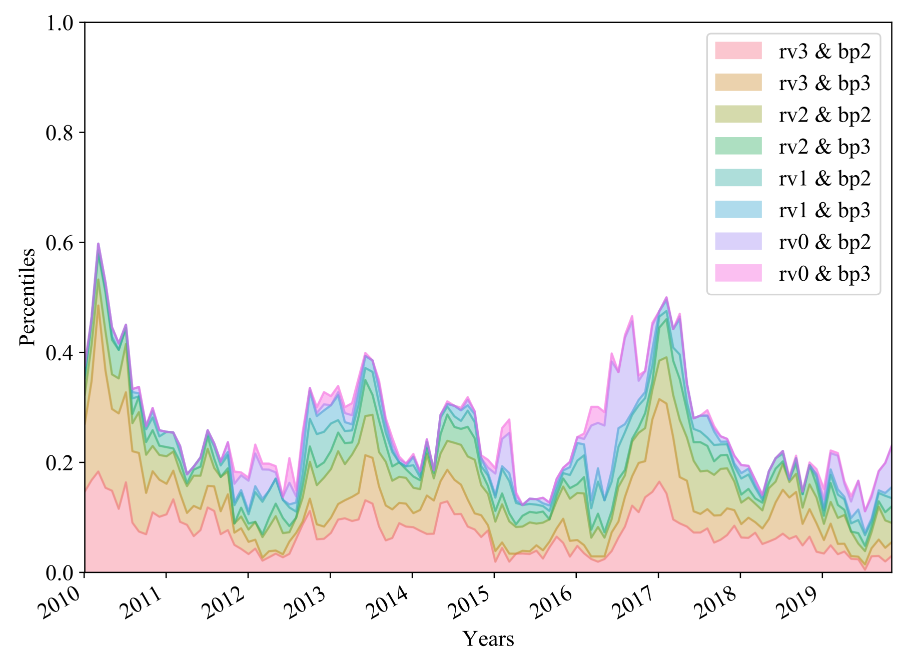
Screening Features for Capturing Anomalies

In parallel with Section 1, this study moves down to the stock level and assesses the impact of firm characteristics within the top momentum decile. The table shows the fractions of quartiles for realized volatility (rv) and the two characteristics, size and book-to-price value (bp), of the Fama- French 3 factor model.

rank	**rv**	**size**	**bp**
0	0.069	0.317	0.480
1	0.125	0.268	0.267
2	0.281	0.235	0.173
3	0.524	0.180	0.079

According to the table, a commanding proportion of stocks within the winners decile subset are concentrated in the top two rv and bottom two bp quartiles. These results suggested to further narrow down the scope to their bivariate quartiles. Their percentage proportion dynamics across the 2010 to 2019 time horizon are shown below:

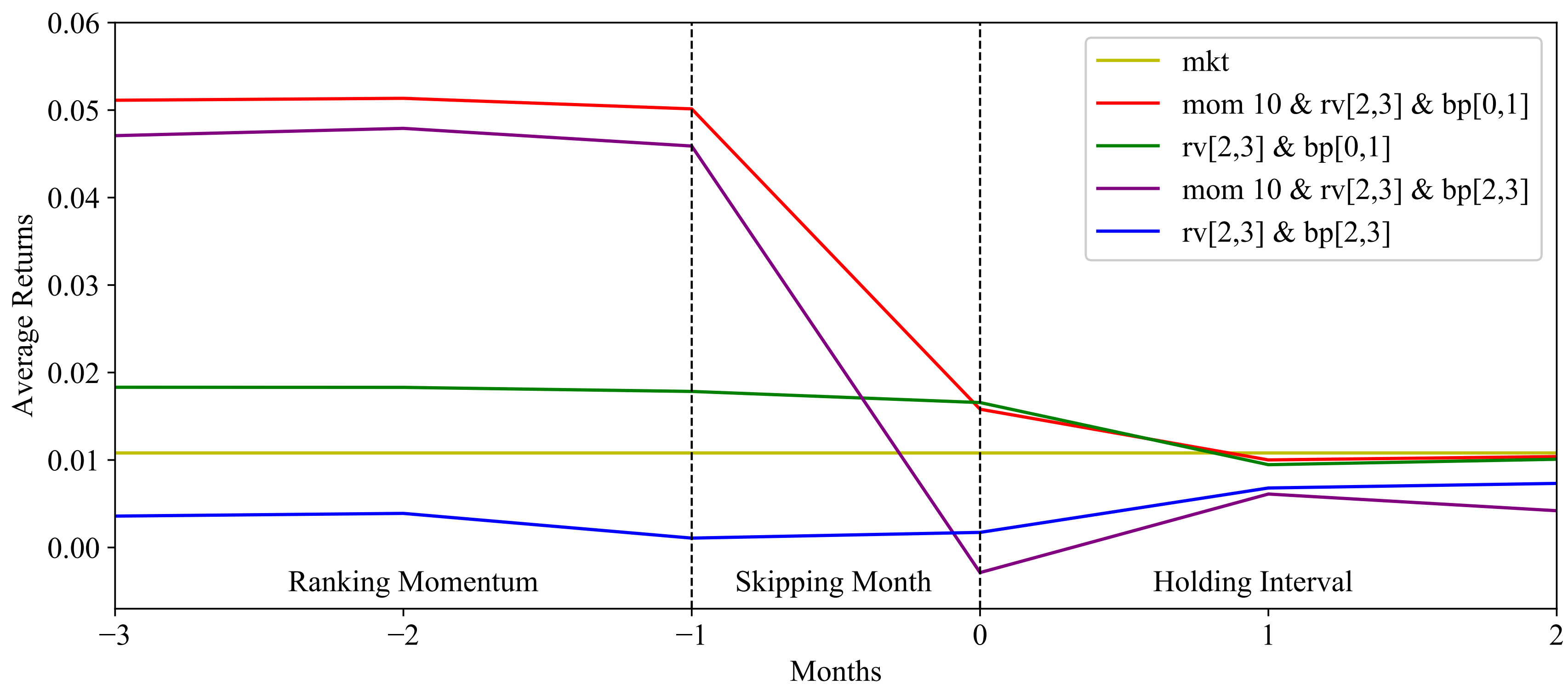




★ The figure shows the dominance of the high realized volatility growth quartile across the time interval with exception to momentum downturns followed by spikes in value-related quartiles. These results suggest that the momentum winners decile represents the sampling of high volatility growth stocks.

Explaining the Momentum Effect for 2011-2019

To pursue the screening results, the high volatility growth and value bivariate quartiles were further evaluated with intertemporal analysis. Below, the figure traces and compares their performance within the momentum winners decile and full sample across the ranking, one-month skipping, and holding intervals.



Starting from the left side, the difference in the ranking period between momentum winners and full sample quartiles is determined by the high idiosyncratic returns sampled by the momentum procedure. Next, during the skip interval as the ranking period ends at lag month -1 on the plot, momentum winners approach the mean level of high volatility stocks. After the formation date, they both experience a similar short-term reversal.

★ To summarize, the intertemporal analysis of the momentum winners decile transparently explains the 2011-2019 momentum premium as the sampling of high volatility growth stocks.

Concluding Remarks

- The source of the momentum premium for 2011-2019 can be transparently explained with intertemporal analysis as the sampling of high volatility growth stocks.

- The results are addressed by a systematic study with a consolidated set of diverse approaches based on the new Zipline-based open-source integrated research platform.

Overview of Platform User Interface: https://flounderteam.github.io/fsharadar/

Examples with FSharadar module: https://github.com/vky-analytics/flounder_sharadar_examples

Scripts for Uncovering Momentum study: https://github.com/ymalitskaia/uncovering-momentum