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Investment viewpoint

From static factors to dynamic styles

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Originated from years of academic research, factors have been building blocks of the systematic equities for quite some time. While their historical track record looks impressive, the recent disappointing performance and violent rotations[1] have raised concerns about the future of factor investing.

The industry and academia has built a line of defence proposing several solutions. Some called for adopting the definition of factors to new realities, proposing, for example, revising book value to include intangibles. Recognising that factors may experience long periods of underperformance, some practitioners turned to timing of factors based on momentum, valuations or macro. Advances in machine learning led to the adoption of new techniques to systematic equities where machines learn the complex predictive relationships between stock attributes (such as Price-to-Book or Return-On-Equity) and their future returns directly skipping the middle man of factors.[2]

The main advantage of machine learning is its ability to discover more complex predictive patterns than those implied by factors. However, using such techniques requires a large amount of data that can only be obtained by looking far back in the history. This reliance on the past makes the strategy not very dynamic as it slowly responses to short-term changes in the market environment.

In this paper, we describe an alternative approach we call 'dynamic styles', that uses the same "low level" stock attributes to predict stock returns. However, instead of building complex predictive models, dynamic styles relies on traditional momentum signals yielding a much more dynamic strategy that can serve as a promising alternative to static factor investing.

[1] We discuss this in our recent paper "Getting Ready for Factor Rotations". All our research is accessible at https://am.lombardodier.com/home/asset-classes/alternatives/alternative-risk-premia/alternative-risk-premia-research.html.
[2] We have been one of the earlier adopters of this approach. See our paper "Machine Learning For the Prediction of Stock Returns".

Harvesting momentum in equity styles

The building blocks of dynamic styles are long-short style portfolios formed on single stock attributes and specific for each region and sector.

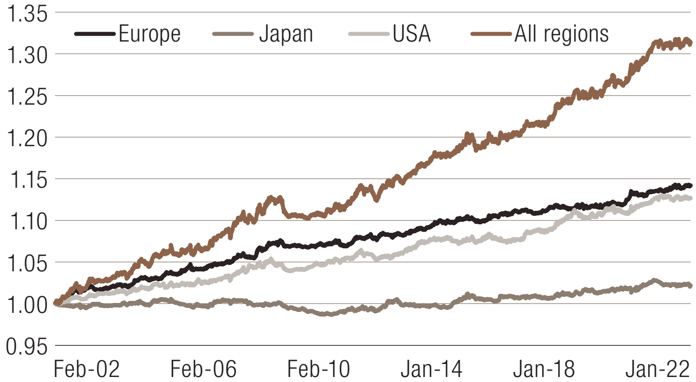
The universe of stocks is defined by the MSCI World index restricted to three major regions: USA, Europe and Japan. For each combination of GICS1 sector, region and stock attribute we form a unique style portfolio by allocating positive weights to the top half stocks with the largest attribute value, and negative weights to the bottom half. For example, for Price-to-Book ratio we form total 33=11×3 portfolios – one per each sector of each region. With such construction, we recognise that different styles may have different trends across regions and sectors. For example, value stocks may trend up in Industrials but not in Health Care. Using the same stock attributes as in our machine learning strategy,[3] we build over 1500 different style portfolios.

In the same away as the CTA[4] industry is taking directional exposures to futures based on recent trends, dynamic styles uses momentum signals to take exposures across style portfolios. At each rebalancing date, we score all the style portfolios according to their returns over several windows less than one year. While each return window has some predictive power, we found that combing several ones makes the model more robust. The scores are then used in a mean-variance optimisation where we seek to maximise the score of the final portfolio of style portfolios subject to a risk constraint.

Exhibit 1 shows the (gross) performance of the global portfolio rebalanced every end of month as well as its regional components. At each rebalancing, the portfolio is sized to have the ex-ante volatility of 1%. We observe that this strategy works well in USA and Europe but less so in Japan. Historically, Japan has been always challenging for factor investing, especially for Momentum.[5]

Dynamic styles uses the stock attributes that are also part of the definition of factors. Therefore, we can expect that the dynamic styles portfolio takes exposures to factors whose attributes are exhibiting strong momentum. As we observe from Exhibit 2, the portfolio indeed can take material factors exposures,[6] which are not constant and tend to change signs over time with the exception of momentum that is always on the positive side. Although the dynamic styles portfolio is not formed directly on the stock momentum, it enters through the backdoor of the style momentum. Looking closely at the evolution of factors exposures, it is interesting to observe that the strategy naturally reduced the exposure to value over last several years but then started building it up since 2021 on the back of recent growth-value rotation.

EXHIBIT 1. PERFORMANCE OF DYNAMICS STYLES



Source: LOIM calculations. For illustrative purposes only.
Past performance is not a guarantee of the future results.

Timing of factors and more

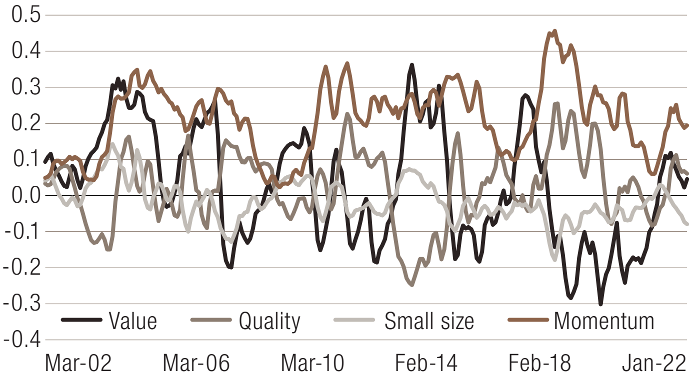
How strong is dynamic styles at timing the factors? To answer this question, we computed the performance of the dynamic styles portfolio attributed to factor exposures. This attribution has been performed region by region using pure factor[7] returns specific to each region. Exhibit 3 suggests that dynamic styles does a good job at timing of factors. This result is striking given that the direct timing of factors has not been found to be particularly successful.[8]

The factor timing does not seem to fully explain the performance of dynamic styles with the residual component adding value too. The residual contribution represents the performance of a factor-neutral long-short portfolio. Its long and short legs have the same exposure to each factor, however, achieved through a different mixture of attributes. We therefore can loosely interpret this residual as the effect of factor definitions.

Performance attribution shown Exhibit 3 summarises the two key characteristics of dynamic styles that distinguish this strategy from factor investing. The first characteristic is the ability to take both positive and negative exposures to factors. For example, we can be short in value while the factor-based portfolio are always long in this factor. The second characteristic is the flexibility in factor definitions. Modern factor investing employs a variety of factor definitions far more complex than the ones used in academic research. For example, we counted 35 different attributes used by the industry to define the 'quality' factor. The multitude of definitions adds to the uncertainty of factor performances and goes somewhat against the philosophy of factors as being sources of simple and robust risk premia. Dynamic styles effectively solves this dilemma through a bottom-up factor construction.

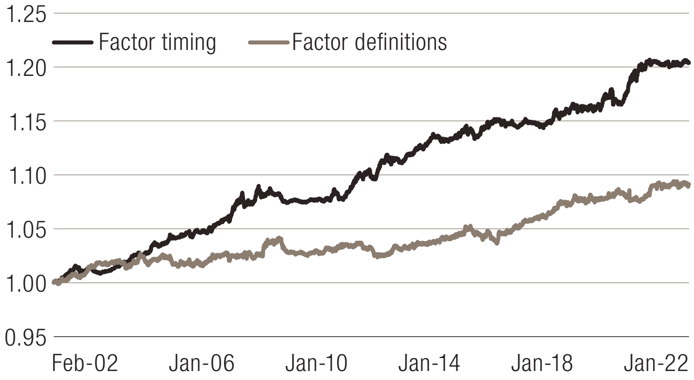
3 We keep only fundamentals attributes and exclude priced-based characteristics such as momentum, reversal, etc.
4 Commodity Trading Advisor.
5 Asness C. 2011. "Momentum in Japan: The Exception That Proves the Rule." *Journal of Portfolio Management* 37(4): 67-75.
6 Factor exposures are measured by z-scores.
7 The details of on pure factor portfolio construction can be found in our paper "Our Approach to Factor Investing".
8 Bender J., X. Sun, R. Thomas, and V. Zdorovtsov. 2018. "The Promises and Pitfalls of Factor Timing." *Journal of Portfolio Management* 44(4): 79-92.

EXHIBIT 2. FACTOR EXPOSURES ARE CHANGING OVER TIME



Source: LOIM calculations. The factor exposures are smoothed over three months. For illustrative purposes only.

EXHIBIT 3. THE STRATEGY IS GOOD BOTH AT FACTOR TIMING AND FACTOR DEFINITIONS



Source: LOIM calculations. For illustrative purposes only.

Conclusion

In this note we presented a new systematic strategy. Dynamic styles takes advantage of momentum in equity styles recognising that styles can behave differently across sectors and regions. Dynamic styles uses the same "low level" stock attributes to characterise equity styles as the ones employed in our machine learning strategy. In our view, the reliance of dynamic styles on momentum only allows it to adopt much quicker to changing environment. Due to its dynamic nature, we consider this strategy a very promising alternative to factor investing.

IMPORTANT INFORMATION