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Discussion of "Target risk strategies for asset allocation and factor investing", Presented by Raul Leote de Carvalho

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Outline

This paper relies on [Perchet et al., 2016] and [Perchet et al., 2014], it deals with **Controlling of the ex-post volatility of a portfolio**.

- It exposes clearly a framework to implement and backtest such **Target Volatility Strategies** ;
- It is largely **model-driven** and relies on **Monte-Carlo Simulations** when it is about in depth investigations;
- And uses **historical data** to comfort obtained conclusions.

Moreover, it explores the added-value of **Factor-Driven Model of Risk**, across different asset classes (Equities, Commodities, FX, Bonds).

Main Principle of the Proposed Approach

Adjust future volatility of the portfolio thanks to a repartition of allocation between the risky asset and cash, using today information

- Potential gain stems from any **relationship between returns and risks** of the underlying assets;
- If returns are independent from anything else you can nevertheless gain on any **risk-driven measure** (like the Sharpe Ratio);
- Gains can be lost if you **ex-ante estimates** are not good enough.
  Mainly if the volatility you estimate today (and uses into your optimization) is not close enough to the realized one tomorrow.

Authors go through a collection of modelled effects:

- Constant **expected returns** (for simulations), or two regimes of expected returns (for historical data);
- Volatility clustering (their α parameter) and **volatility** persistence (their β parameter); $\alpha + \beta \simeq 100\%$;
- Gaussian or Fat Tails for the **innovations** (not predictable part of the returns) and / or **negative correlation** between returns and volatility (intense returns linked to low volatility –GJR-Garch–; this is not the *low-volatility anomaly* [Ciliberti et al., 2015]; nor an increase of correlations of assets during market crashes).

As expected controlling the volatility has an impact on risk-driven measures, like the **Sharpe Ratio** (you try to decrease its denominator).
Nevertheless you face a **Frequency Issue**: if the volatility changes each year and you use the yearly volatility to allocate for next year... You will never do what you think.

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I have a technical reserve about SR for regime switching contexts, they do not average or change scale easily, cf. [Lo, 2002].

When you try to control a quantity ex-ante (here the volatility), It is better to **have good estimates** .

- On presented Tables, results seem to improve (rebalancing frequency?);
- Forecasting volatility is of paramount importance: remember **volatility is rough** [Gatheral et al., 2014]. As a rule of thumb: *to predict volatility for the next year, you need to use one past year of data*.
- Authors choose to model assets using a **Markov chain regime switching model** with two regimes. What if you use only one regime?

Remarks:

- The ex-post volatility seems to be always larger than the ex-ante target. It is the *curse of over-estimating future risks* explored for multi-dimensional portfolios? cf. [Laloux et al., 1999].
- In any case, if it is about running a numerical optimization, I would recommend to **target a quantile of volatility** (i.e. a maximum of volatility), and not an average.

Authors compare the target volatility portfolios **across asset classes** and note **it works better with risky assets**.

Moreover, they use a **Factor Decomposition** of each asset class (Momentum vs. Values) to control the risk on each factor

- Reminder: Factors have a (good) mix of risk–return (compared to Sectors, for instance, cf. [Briere and Szafarz, 2015]);
- It is on the path to **Risk Budgeting** : You allocate a risk budget per factor, cf. [Roncalli, 2014];

It is always difficult to organize a dialog between models, data and simulations:

- **Simulations**, i.e. on "fake data", generated by Monte-Carlo (MC) simulations according to the stated model, are good to check you are going into the wanted directions.
- **Backtests**, i.e. on historical data (less data than for MC simulations) are very important to account for effects that are not in the model (mainly the i.i.d. assumptions).
- **Stress-tests** are very interesting too: what about the **robustness of your methodology** to other modelling assumptions (use MC generated by other models)?, or what about looking at other metrics?

- **Ex-ante risk control** is important and useful, hence I like a lot this Target Volatility Strategy;
- Especially for **metrics involving risk** ;
- And more when returns and risks are correlated a nice way (for instance volatility increases if returns are down), but you need to react at the proper speed.
- **Factors are good candidates** to drive such risk control methodology (remember Richard Roll call them "risk drivers" [Pukthuanthong and Roll, 2014]);
- **Rebalancing frequency is not a detail** ; it has to dialog well with your estimates (volatility if rough), and with the rhythm of the relationship between returns and risk.

Briere, M. and Szafarz, A. (2015).
Factor-Based v. Industry-Based Asset Allocation: The Contest.
Social Science Research Network Working Paper Series.

Ciliberti, S., Lemperiere, Y., Beveratos, A., Simon, G., Laloux, L., Potters, M., and Bouchaud, J.-P. (2015).
Deconstructing the Low-Vol Anomaly.
Social Science Research Network Working Paper Series.

Gatheral, J., Jaisson, T., and Rosenbaum, M. (2014).
Volatility is Rough.
Social Science Research Network Working Paper Series.

Laloux, L., Cizeau, P., Bouchaud, J. P., and Potters, M. (1999).
Noise Dressing of Financial Correlation Matrices.
Phys. Rev. Lett., 83(7):1467–1470.

Lo, A. W. (2002).
The statistics of Sharpe ratios.
Financial Analysts Journal, 58(4):36–52.

Perchet, R., Carvalho, R. L., and Moulin, P. (2014).
Inter-Temporal Risk Parity: A Constant Volatility Framework for Factor Investing.
Social Science Research Network Working Paper Series.

Perchet, R., de Carvalho, R. L., Heckel, T., and Moulin, P. (2016).
Predicting the Success of Volatility Targeting Strategies: Application to Equities and Other Asset Classes.
The Journal of Alternative Investments, 18(3):21–38.

Pukthuanthong, K. and Roll, R. (2014).
A Protocol for Factor Identification.
Social Science Research Network Working Paper Series.

Roncalli, T. (2014).
Introduction to Risk Parity and Budgeting.