Dynamic Regime Strategy for Stress Testing and Optimizing Institutional Investor Portfolios

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Abstract

After the 2008 financial crisis diversification failed being immune to large drawdowns because correlations between risky assets tends to strengthen during times of crisis. Our work aims to develop a stand-alone trading system to construct portfolios that show the benefits of value and momentum style integration and presents the effectiveness of alternative integration methods for long-only absolute return funds, which seeks absolute returns that are not highly correlated to traditional assets such as stocks and bonds. Our strategy will integrate four primary themes; diversification by risk, volatility targeting, momentum and trend-following, and extreme valuation and in the same order these four themes will contribute to risk on final portfolio to reduce a long-biased portfolio's exposure to episodic drawdowns. This work will use daily and monthly closing value of economic indicators, stocks, futures, commodity contracts, listed real estate, high-yield bonds, inflation-linked bonds, and government bonds from developed and emerging market to avoid correlation among the assets like stocks and bonds. We are planning to use the CRoss Industry Standard Process for Data Mining (CRISP-DM) model to guide the necessary steps, processes, and workflows for executing our project.

Keywords: *CRISP-DM; alternative risk premia; regime-switching; portfolio optimization; dynamic asset allocation*

1. Introduction

In the aftermath of that global financial crisis, institutional investors were concerned about the inherent volatility of equity markets (Wurtz, 2018). At the same time, the introduction of ultra-low monetary policy has worsened those concerns, with their liabilities increasing as bond rates fell. In addition, these investors typically have liabilities with varying horizons tied to duration or cash flows. In order to best meet the needs of shareholders, many institutional investors look to hedge funds to provide another source of diversifying returns for their portfolios. The 2008 financial crisis clearly showed that diversification was not sufficient to avoid large drawdowns (Nystrup et al. 2017). As diversification failed, when it was needed the most, because correlations between risky assets tends to strengthen during times of crisis (Boyd, et al., 2017).

These challenges have provided a fertile ground for disruptive financial innovations that are significantly affecting the investment and asset management industry (Kahn & Lemmon, 2016). For instance, institutional investors are now able to choose an exchange-traded fund (ETF) that will systematically select stocks with characteristics like low volatility and growth at lower cost. Wurtz (2018) observes that the development of the exchange-traded fund (ETF) wrapper and the ability of asset managers and index providers to handle higher quantities of data, has resulted in more choices for institutional investors. With, more choices institutional investors can now choose quantitative investment strategies that span the spectrum of market risk to active risk. Quantitative investment strategies have evolved into four general approaches to diversifying and helping to mitigate equity risk: 1) long Treasuries, 2) trend-following, 3) tail risk hedging and 4) alternative risk premia diversifiers, such as carry and value strategies (Baz, Davis, Sapra, Tsai, & Gillmann, 2019).

Our project locates within the growing alternative risk premia (ARP) strategies, which according to Carroll & Ramaswamy (2018), seeks absolute returns that are not highly correlated to traditional assets such as stocks and bonds. The ARP strategies continue to evolve with the development of new methods and techniques to sharpen existing signals and systematically extract premia from expensive "hedge" fund strategies. Given the increased complexity and diversity of these strategies, our project will build on a blend of fundamental and technical analysis frameworks and literature guided by Carroll & Ramaswamy (2018) ARP framework and the Baz et al.'s (2019) Theoretical Framework for Equity-Defensive Strategies. While, the project contributes to recent and growing literature on dynamic asset allocation for varied financial markets under regime switching frameworks (Bae, Kim, & Mulvey, 2014; Nystrup, Hansen, Madsen, & Lindström, 2015, 2018; Kotsalis & Lan, 2018; Fons, Dawson, Yau, Zeng, & Keane, 2019), style integration for assets (Fitzgibbons et al., 2016; DeMiguel et al., 2017; Fernandez-Perez, Fuertes, & Miffre, 2017) and time-varying portfolio optimization (Chakravorty, Awasthi, Da Silva, & Singhal, 2018; Dangl & Weissensteiner, 2018; Platanakis, Sakkas, & Sutcliffe, 2019; Jin, Chen, & Yuan., 2019).

Our project's competitive edge is leveraging from the fact that many of the portfolios of institutional investors fall under two extreme spectrum of investment strategies. With one end having most common risk premium, that is based Long only strategy, which involves high capacity and low-cost allocations that are extremely sensitive to market directional risk and macroeconomic sensitives (Wurtz, 2018); and on the other end extremely differentiated strategies like convertible arbitrage, managed futures, and merger arbitrage etc., low capacity and high cost allocations that have almost zero market directional risk and macroeconomic sensitives due to their idiosyncratic nature (Lester, 2017).

Our opportunity is to create an absolute return strategy that fit between these two extremes which can diversify an institutional investor's exposure to long only market betas, yet lacks the drawbacks of some of the most sophisticated hedge fund strategies such as significant cost, illiquidity, and capacity constraints (Kahn & Lemmon, 2016). The competition comes not only from the Institutional investor who desire absolute return strategies to diversify the majority of the risk in their portfolios, also from asset managers competing to garner similar risk premiums (Moore, 2015). When competing with these competitors, the differentiator of our approach is thoughtful implementation to portfolio construction and how our integrated approach creates a more robust absolute return strategy without depending on a single return driver.

2. Aims and Objectives

Our project aims to develop a portfolio allocation framework that show the benefits of value and momentum style integration and presents the effectiveness of alternative integration methods for long-only absolute return funds. The framework is flexible enough to be applicable to any asset class for either long-short, long- or short-only styles in line with Fernandez-Perez, Fuertes, & Miffre's (2017) approach. The project output is a stand-alone trading system, that can be classified as Alternative risk premia (ARP) strategy, which uses a portfolio construction philosophy rooted in the principles of consistency, diversification, and downside protection. Specifically, we draw on three building blocks; a timing portfolio, construction portfolio, and combining them in order to pursue a range of risk and return objectives. Each component or portfolio is built from the bottom up with a specific objective in mind. For instance, we will generate our portfolios with exposure to risk factors widely acknowledged in academia such as Value, Size, Quality, Momentum and Low Volatility (Mikaelsson & Nilsson, 2017).

3. Methodology

This section provides a description of the data and methodology used in the project. It starts by describing the data followed by the portfolio generation section, which is intended to explain the portfolio selection, scoring and weighting process. This is then followed up by tools used and the timeline the project.

3.1 The data

The asset universe considered for this project consists of daily or monthly closing prices of developed (DM) and emerging market (EM) economic indicators, stocks, futures, commodity contracts, listed real estate, DM and EM high-yield bonds, inflation-linked bonds, and government bonds. The large universe is used in seeking absolute returns that are not highly correlated to traditional assets such as stocks and bonds. In addition, data accessibility availability is usually a challenge, therefore we create a data preprocessing notebook that we will use to explore the data to get assets or indices that will improve our diversification. Most of the data collected for our asset universe is available from Asset Macro, Quandl and Thomson Reuters DataStream websites. All indices measure the total net return in USD covering the period from 2008 through 2018.

3.3 Tools and Model

Our project uses the CRoss Industry Standard Process for Data Mining (CRISP-DM) model to guide the necessary steps, processes, and workflows for executing our project right from formalizing business requirements to testing and deploying a solution to transform data into insights (Sarkar, Bali, & Sharma, 2018). The CRISP-DM model entail building an end-to-end solution by following six major steps or phases, some of them being iterative. The lessons learned during the process can trigger new, often more focused business questions, and subsequent data mining processes will benefit from the experiences of previous ones. While our modelling will follow the standard Machine Learning pipeline in Figure 1(Sarkar, Bali, & Sharma, 2018). we will follow the plan attached in appendix A

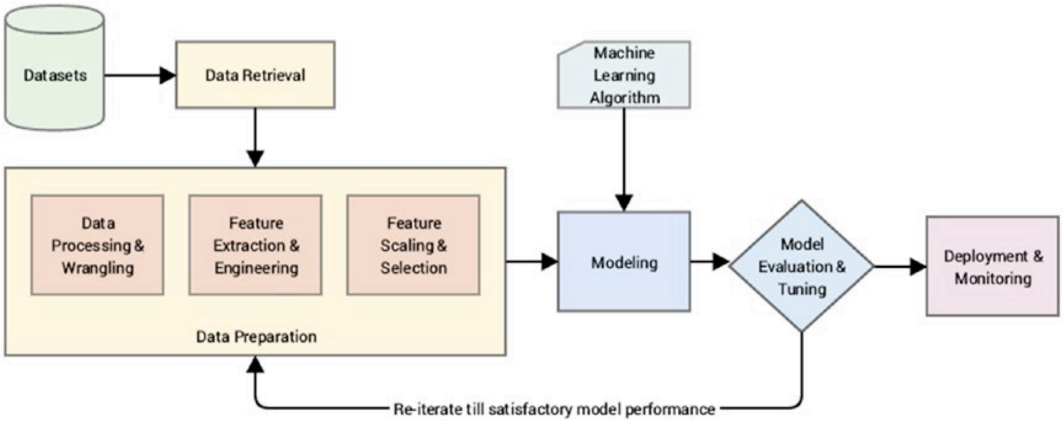

Figure 1: Standard Machine Learning pipeline
Source: (Sarkar, Bali, & Sharma, 2018)

3.2 Portfolio Construction

The portfolio we are building is one that will look to reduce a long-biased portfolio's exposure to episodic drawdowns concurrent with, or precluded by extreme changes in volatility and valuation. The strategy will integrate four primary themes; diversification by risk, volatility targeting, momentum and trend-following, and extreme valuation. The contribution to risk on a total portfolio basis will be the largest for diversification by risk, progressing to the smallest for extreme valuation. We will lay out the following horizontal "layers" as if they were a pyramid where the tip of the pyramid would be the total portfolio integrated as one, and represented by the highest number. The components of each layer are described in Figure 1 below:

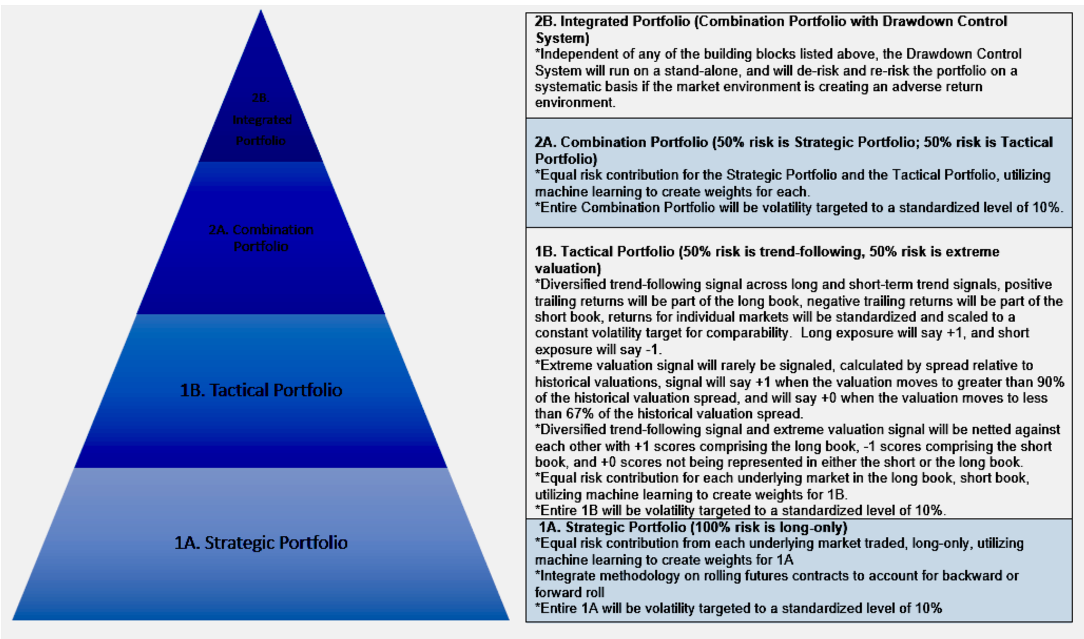

Figure 2: Portfolio Construction

Figure 1 shows the summary of our approach to portfolio construction using the following modelling themes:

Model Z. Diversify by Risk (largest contribution, least time period centric)

Our first step in adopting to regime changes would be to diversify the portfolio by risk. This theme will be pervasive across the portfolio and will help our strategy in reducing its exposure and dependency to a shock felt in one or a few specific markets.

Model Y. Volatility Targeting
Our second step in adopting to regime changes would be to target a constant level of volatility at each layer of the strategy as well as each subcomponent, most notably, 1A and 1B. While "Diversifying by Risk" in Z should help our strategy from suffering when a specific market we trade moves in a dramatically different fashion from the others, it doesn't help us reduce losses when all of our markets in aggregate begin to exhibit materially different profiles from their long-term averages. If on average, all the markets we trade roughly double in risk over a shorter-term time period, it won't matter if we are diversifying by risk as stated in Z, because our portfolio will be much more risky than desired. Volatility Targeting will help us solve for the shortcomings of Z, "Diversification by Risk."

Model X. Momentum and Trend-Following
Our third step in adopting to regime changes would be to have a strategy that helps us to determine when the core of our portfolio, the Strategic Portfolio, could be particularly vulnerable, due to the fact that it is long-only. While we want to be long-biased since we can earn the market premiums tied to investing in various asset classes, shorter-term time periods such as the great depression and the financial crisis can destroy decades of compounded return. Because of this, we want to have a signal less driven by a risk premium as with our Strategic Portfolio, but more driven by a behavioral tendency. The Strategic Portfolio will also be driven by very long-run assumptions, while this piece, will be driven by shorter and more medium-term market environments. This "market beta filter" will help us to determine when the long-only exposures of Z and Y could leave our portfolio particularly exposed to large losses.

Model W. Extreme Valuation (smallest contribution, most time period centric)
Our fourth step in adopting to regime changes would be to have a signal that helps us solve for some of the factors that would leave our Momentum and Trend-Following signals contained within X, particularly vulnerable. While the signals contained with X do a great job at helping filter when it may not be the most advantageous to have long-only exposures, these signals can suffer episodic losses tied to a sharp reversal in sentiment, many times driven by news. This is most exemplified in the spring of 2009 when trends sharply reversed on news of strong central bank intervention. This counter-trend signal will help reduce the vulnerability of the momentum and trend-following signals highlighted in X, and will tell us that even through the behaviorally driven trends are still largely negative, that those signals could be particularly vulnerable to sharp reversals due to the markets being traded being excessively cheap in valuation. Because the signal will only kick in during the most extreme times, this signal will be most acutely targeting regime changes such as in the spring of 2009 which would have caused outsized losses for our momentum and trend-following.

Model Z should be the most robust, while having the least to do with a specific return environment tied to a sharp change in regime. On the other end of the spectrum, W should be the closest to a true change in regime signal, and should have the most to do with creating profitability and/or reducing losses tied to an episodic change in market regime. Model W (Extreme Valuation) should solve for vulnerabilities in Model X (Momentum and Trend Following) when sharp reversals in sentiment cause outsized losses.

Model X (Momentum and Trend Following) should solve for vulnerabilities in Model Y (Volatility Targeting) when broad based asset class declines still create losses for the portfolio. With asset classes declining and the signals in Model Y (Volatility Targeting) reducing broad market, that side of the portfolio is long-only and remains exposed to declining asset prices.

Model Y (Volatility Targeting) should solve for vulnerabilities in Model Z (Diversification by Risk) when the level of risk broadly in the portfolio or within specific markets deviate from their longer-term averages. We want to make sure to have a consistent exposure to long-term risk premiums, regardless of changing environments and the underlying deviation from long-run assumptions.

Model Z (Diversification by Risk) should solve for the fact that we want to be the least susceptible idiosyncratic risk driven by any one market, but that we want to capture the risk premiums in any of the markets we trade in the most all-weather fashion, and regardless of the differences between different markets, most notability in multi-asset portfolios.

Total Portfolio (Drawdown Control System) should solve for the fact that no matter how strong or robust our portfolio's signals are, we fully understand that we could experience time periods of sustained underperformance. Regardless if this underperformance is driven by a changing market regime or simply by an adverse return environment for the markets we trade, humility in reducing broad market exposure when everything seems to not be working, is the most prudent course of action.

4. Conclusion

The aim of this project is to design a standalone absolute return trading system with significant reduction in directional market risk and macroeconomic sensitivities to optimize institutional investor portfolios. Our program should have the additional benefit of not only exhibiting a more constant risk profile, but also reducing the probability of an outsized stress loss, fostered by a significant external shock. As such, our commitment is to develop an absolute return-oriented trading system that would aid institutional investors in dynamically adapting their portfolio exposures to the prevailing market risk environment. Our program will also help in managing downside tail risk through a proactive drawdown control system, that will achieve higher risk-adjusted returns regardless of changing economic conditions. Most importantly, our program's complementary blending of deep value and momentum styles, along with a strong focus on balanced risk control, will help institutional investors in meeting their obligations through modest high returns and limited drawdown risk.

References

Amihud, Y., Mendelson, H., & Pedersen, L. H. (2013). *Market liquidity : asset pricing, risk, and crises.* Cambridge: Cambridge University Press.

Bae, G. I., Kim, W. C., & Mulvey, J. M. (2014). Dynamic asset allocation for varied financial markets under regime switching framework. *European Journal of Operational Research, 234*(2), 450-458.

Baz, J., Davis, J., Sapra, J., Tsai, J., & Gillmann, N. (2019, May). A Theoretical Framework for Equity-Defensive Strategies . *PIMCO Quantitative Research*.

Boyd, S., Busseti, E., Diamond, S., Kahn, R. N., Koh, K., Nystrup, P., & Speth, J. (2017). Multi-period trading via convex optimization. *Foundations and Trends® in Optimization, 3*(1), 1-76.

Brown, A. (2011). *Red-blooded risk: the secret history of Wall Street.* New Jersey: John Wiley & Sons.

Brown, A. (2016). *Financial risk management for dummies.* Chichester, West Sussex: John Wiley and Sons, Inc.

Carroll, R., & Ramaswamy, R. (2018, March). Overview of Alternative Risk Premia ("ARP") Strategies. *White Paper*. Breton Hill: Neuberger Berman.

Chakravorty, G., Awasthi, A., Da Silva, B., & Singhal, M. (2018). Deep Learning based Global Tactical Asset Allocation. *Research Gate*. Retrieved from https://www.researchgate.net/profile/Gaurav_Chakravorty/publication/328907909_Deep_Learning_for_Global_Tactical_Asset_Allocation/links/5c80e153299bf1268d407d37/Deep-Learning-for-Global-Tactical-Asset-Allocation.pdf

Dangl, T., & Weissensteiner, A. (2018). Optimal Portfolios under Time-Varying Investment Opportunities, Parameter Uncertainty and Ambiguity Aversion. *SSRN*. Retrieved from https://ssrn.com/abstract=2883768 or http://dx.doi.org/10.2139/ssr

Eurekahedge. (2003, August). *Long-Only Absolute Return Funds Enter the Alternative Investment Universe (Series 1 of 2).* Retrieved from Eurekahedge: http://www.eurekahedge.com/Research/News/1384/03aug_archive_long_only

Fernandez-Perez, A., Fuertes, A. M., & Miffre, J. (2017). Harvesting Commodity Styles: An Integrated Framework. *Working Paper*.

Fons, E., Dawson, P., Yau, J., Zeng, X. J., & Keane, J. (2019). A novel dynamic asset allocation system using Feature Saliency Hidden Markov models for smart beta investing. *arXiv preprint, arXiv:1902.10849*.

Ilmanen, A. (2011). *Expected returns : an investor's guide to harvesting market rewards.* Chichester, West Sussex, U.K: Wiley, 2011.

Jin, X., Chen, N., & Yuan., Y. (2019). Multi-period and tri-objective uncertain portfolio selection model: A behavioral approach. *The North American Journal of Economics and Finance, 47*, 492-504.

Kahn, R. N., & Lemmon, M. (2016). The Asset Manager's Dilemma: How Smart Beta Is Disrupting the Investment Management Industry. *Financial Analysts Journal*. doi:10.2469/faj.v72.n1.1

Kotsalis, G., & Lan, G. (2018). Robust Optimization under Regime Switching. *arXiv preprint, arXiv:1801.00170*.

Lester, A. (2017). *Primer: the factor drivers of investment returns* . Schroders.

Maguire, P., Moffett, K., & Maguire, R. (2018). Combining Independent Smart Beta Strategies for Portfolio Optimization. *arXiv preprint, arXiv:1808.02505.*

Mikaelsson, A., & Nilsson, M. (2017). Smart Beta Factor Investing: Enhancing risk-adjusted returns with exposure to risk factors and empirical evidence of market inefficiencies. *Masters Thesis*. Lund University School of Economics and Management.

Moore, H. (2015, September). *An Institutional Investor Sponsored Report on Smart Beta: From Theory To Practice* . Retrieved from Institutional Investor: https://www.institutionalinvestor.com/images/416/SMART%20BETA%20(Reprint-Complete)

Nystrup, P., Hansen, B. W., Madsen, H., & Lindström, E. (2015). Regime-based versus static asset allocation: Letting the data speak. *Journal of Portfolio Management, 42*(1), 103.

Nystrup, P., Madsen, H., & Lindström, E. (2018). Dynamic portfolio optimization across hidden market regimes. *Quantitative Finance, 18*(1), 83-95.

Pedersen, L. H. (2015). *Efficiently inefficient: how smart money invests and market prices are determined.* Princeton: Princeton University Press.

Platanakis, E., Sakkas, A., & Sutcliffe, C. (2019). The role of transaction costs and risk aversion when selecting between one and two regimes for portfolio models. *Applied Economics Letters, 26*(6), 516-521.

Sarkar, D., Bali, R., & Sharma, T. (2018). *Practical Machine Learning with Python. A Problem-Solvers Guide To Building Real-World Intelligent Systems.* Berkely: Apress.

Tulchinsky, I. (2015). *Finding alphas : a quantitative approach to building trading strategies.* Chichester: John Wiley and Sons.

Wurtz, F. (2018, October). *Factor investing & smart beta: The smart beta (r)evolution.* Retrieved May 22, 2019, from Investments & Pensions Europe: https://www.ipe.com/reports/special-reports/etfs-guide/factor-investing-and-smart-beta-the-smart-beta-revolution/10027012.article

Appendix A

Phases	Research Focus	Emphasis	Modular Breakdown	Principal Tasks	Est Time	Submissions	Deadline
Scope Phase	Exploration	Descriptive Study	1. Identify your research problem (2 weeks)	Ideation Literature searches and defining project Data Preparation and accessability Scope Validation	2 weeks	1. Problem Statement	13-May-19
Research Phase	Observation	Focused Study	2. Analysis (2 weeks) 3. Design (2 weeks) 4. Review 1 (1 week)	Review and organize information Data Exploration Retrieve and evaluate sources Literature and solutions review Data Preparation and accessability Scope Validation	5 weeks	1. Literature Review and Competitor Analysis 2. Project Proposal 3. Peer Review	27-May-19 10-Jun-19 20-Jun-19
Development Phase	Preparation and Iteration	Selective Study	5. Develop (2 weeks) 6. Implement (3 weeks)	Development and Testing framework setup Model Development Early Stage Assessments	5 weeks	1. Status Update 2. Peer Review 3. Draft Project	24-Jun-19 29-Jun-19 15-Jul-19
Deployment Phase	Submit & Present	Research Text	7. Submit & Present	Productization and Monitoring Late stage review Project submission	1 weeks	1. Final Project Report and Presentation	5-Aug-19