The Hod Group is a financial advisory firm in Luxembourg that advises on asset allocation and portfolio implementation, among other financial matters. The Hod Group employs a full-scale optimization routine in their portfolio construction across 10 index funds, covering six asset classes: equities, bonds, commodities, real estate investment trusts, hedge funds, and risk-free. Full-scale optimization allows The Hod Group to optimize weights on these 10 index funds to maximize expected client utility. This approach is in contrast to the classic mean-variance optimization that determines portfolio weights by maximizing the expected return for a given level of volatility. One drawback of mean-variance optimization is its focus on the first two moments of a returns distribution. Said another way, mean-variance optimization does not fully consider higher order moments, e.g., the potential for large losses, which is of particular concern for The Hod Group's clientele.

To capture loss aversion in their full-scale optimization, The Hod Group employs a log-wealth utility function to model their client's utility as a function of portfolio returns. In a log-wealth utility function, the absolute value of the marginal increase in utility after exceeding a target return is less than the absolute value of marginal utility decrease from failing to meet a target return. Because they are able to penalize their optimization routine for large losses, The Hod Group is able to reduce drawdowns compared to their benchmarks.

Every month, this optimization routine yields specific portfolio weights for each of the 10 investable index funds. The Hod Group manages three portfolios with different risk tolerances: Low, Medium, and High Risk. The goal of this analysis is to study signals that suggest when to dynamically shift weights in each index to the risk-free asset, in an effort to further reduce overall portfolio risk. In effect, we seek to identify signals that are informative for predicting when markets are trending downward and when there is increased systematic risk in markets.

III Data

The following analysis draws upon publically available data sources to examine the potential portfolio improvements from a tactical overlay. The time series of returns and relative weights for a pre-existing strategic asset allocation framework serve as the starting point for our analysis. Investable assets within that framework are trade-able net return indices. Momentum signals are computed based on the time series of asset returns. Sector data from Bloomberg and DataStream serve as the basis for the computation of disruption signals.

what are disruption signals??

Hod Group Investable Assets

Asset Class	*Bloomberg Ticker*	*Description*
US Equities	NDDUUS Index	MSCI Daily Total Return Net USA
International Equities	NDDUEAFE Index	MSCI Daily Total Return Net EAFE (Europe, Australasia, and Far East)
Emerging Market Equities	NDUEEGF Index	MSCI Daily Total Return Net Emerging Markets
Low Beta Equities	NDUEACWF Index	MSCI AC World Daily Total Return Net (65%); EONIA (35%)
European Government Bonds	JPMGEMLC Index	J.P. Morgan Economic and Monetary Union Government Bond Index
Corporate Bonds	JMRTIG Index	J.P. Morgan Credit Index Investment Grade
Real Estate	FNERTR Index	FTSE NAREIT All Equity REITS Total Return Index
Commodities	SPGCCITR Index	S&P Goldman Sachs Commodity Index (GSCI) Official Close Total Return Index
Hedge Funds	HFRXGLE Index	HFRX Global Hedge Fund Index
Cash	EONCAPL7 Index	Euro OverNight Index Average (EONIA): Effective overnight interest rate as a weighted average across specific European banks, in Euros

External Data

how SMA calculated?

The time series momentum trigger relies on daily returns from the indices above, while the simple moving average trigger relies on the index level (constructed from returns data, starting from a baseline 100). For the absorption ratio analysis, we analyze ten different sector indices within each MSCI equity index. For example, within the MSCI USA Equity Index, we apply the absorption ratio analysis to indices based on ten USA sector indices, e.g., energy, financial, health care etc. For US sector data, we use Data Stream because it has data going back to 2004, whereas Bloomberg does not. However, Bloomberg does have sector index data going back to 2004 for Europe (as a proxy for MSCI EAFE), world, and emerging markets. We will use Bloomberg data provided by The Hod Group for the absorption ratio analysis involving EAFE, World, and emerging markets. The tables below summarize the sector data used for the absorption ratio analysis:

MSCI World Index	
Bloomberg Ticker	***Description***
M1WO0CD Index	MSCI World Consumer Discretionary Net Return USD Index
M1WO0CS Index	MSCI World Consumer Staples Net Return USD Index
M1WO0EN Index	MSCI World Energy Net Return USD Index
M1WO0FN Index	MSCI World Financials Net Return USD Index
M1WO0HC Index	MSCI World Health Care Net Return USD Index
M1WO0IN Index	MSCI World Industrials Net Return USD Index
M1WO0IT Index	MSCI World Information Technology Net Return USD Index
M1WO0ML Index	MSCI World Materials Net Return USD Index
M1WO0TC Index	MSCI World Telecommunication Services Net Return USD Index
M1WO0UL Index	MSCI World Utilities Net Return USD Index

MSCI Emerging Markets Index	
Bloomberg Ticker	***Description***
M1EF0CD Index	MSCI Emerging Markets Consumer Discretionary Net Return USD Index
M1EF0CS Index	MSCI Emerging Markets Consumer Staples Net Return USD Index
M1EF0EN Index	MSCI Emerging Markets Energy Net Return USD Index
M1EF0FN Index	MSCI Emerging Markets Financials Net Return USD Index
M1EF0HC Index	MSCI Emerging Markets Health Care Net Return USD Index
M1EF0IN Index	MSCI Emerging Markets Industrials Net Return USD Index
M1EF0IT Index	MSCI Emerging Markets Information Technology Net Return USD Index
M1EF0MT Index	MSCI Emerging Markets Materials Net Return USD Index
M1EF0TC Index	MSCI Emerging Markets Telecommunication Services Net Return USD Index
M1EF0UT Index	MSCI Emerging Markets Utilities Net Return USD Index

MSCI USA Index	
DataStream Ticker	***Description***
MSU5CD$(NR)	MSCI US IMI/Consumer Discretionary 25 – 50 Net Return in Euros
MSU5CS$(NR)	MSCI US IMI/Consumer Staples 25 – 50 Net Return in Euros
MSU5E1$(NR)	MSCI US IMI Energy Net Return in Euros
MSU5FN$(NR)	MSCI US IMI Financials Net Return in Euros
MSU5HC$(NR)	MSCI US IMI Health Care Net Return in Euros
MSU5ID$(NR)	MSCI US IMI Industrials Net Return in Euros
MSU5IT$(NR)	MSCI US IMI Information Technology Net Return in Euros
MSU5M1$(NR)	MSCI US IMI Materials Net Return in Euros
MSU5T1$(NR)	MSCI US IMI Telecommunication Services Net Return in Euros
MSU5U1$(NR)	MSCI US IMI Utilities Net Return in Euros

This section outlines the computation and application of tactical signals to dynamically adjust portfolio weights to better protect against risk without substantially eroding portfolio returns. We employ three signals designed to avoid exposure to major drawdowns in asset prices discussed in the Literature Review above. These signals are: (1) the Absorption Ratio (AR), (2) Time Series Momentum (TSMOM), and (3) a Simple Moving Average Crossover (SMA). The individual process for generating and analyzing each of these triggers is outlined below, followed by a discussion of how these may be used in concert to create informed deviations from existing time-varying asset weights.

Absorption Ratio

As explained in the literature review, the AR is designed to measure market fragility. Explained another way, the AR is designed to measure when markets are becoming more and more correlated, and therefore prime for a major drawdown. Each of the equity indices in our investible universe can be represented by a collection of index funds following specific sectors. For example, with the MSCI USA Equity Index, we apply the AR analysis to ten sector indices that follow USA consumer staples, USA consumer discretionary, and USA energy etc. Therefore, the AR trigger recognizes when sectors within an equity index are becoming increasingly correlated. Hence, we want to shift the portfolio weight from the equity index to cash as we see a sharp increase in correlation between sectors.

To calculate the AR, every day we look back over the previous 500 days and calculate an exponentially weighted covariance matrix, for the ten sectors, with a half-life of 250 days. Once the weighted covariance matrix is calculated, we observe the ratio of the sum of the first two eigenvalues to the total variance:

$$AR_t = \frac{\lambda_1 + \lambda_2}{\sum_{i=1}^{N} \sigma_i}$$

$$\lambda_{1,2} = 1^{st} and\ 2^{nd}\ eigenvalues$$
$$N = number\ of\ sectors$$
$$\sigma_i^2 = Variance\ of\ the\ i^{th}\ sector$$

Finally, since we are looking for jumps in the AR, we define ΔAR as the difference between the 15-day moving average of AR and the 252-day moving average of AR, standardized by the 252-day moving standard deviation:

$$\Delta AR_t = \frac{AR_{t,15-Day\ MA} - AR_{t,252-Day\ MA}}{\sigma_{AR:previous\ 252\ days}}$$

The observed time series of changes in the absorption ratio is used to infer how much of a position in a risky asset should be allocated to the risk-free asset at each point in time. The changes in the absorption ratio can be translated into a binary signal as follows

$$\Delta AR_t^b = \begin{cases} 0 : \Delta AR_t < 1 \\ 1 : \Delta AR_t \geq 1 \end{cases}$$

To analyze the stand-alone impact of utilizing changes in the absorption ratio to deviate from existing asset weights, we also consider the following shifts (as percentages expressed in decimal notation) from positions in risky assets to positions in the risk-free asset:

$$Shift_t = \begin{cases} 0.00 : \Delta AR_t \leq -1 \\ 0.50 : \Delta AR_t < |1| \\ 1.00 : \Delta AR_t \geq 1 \end{cases}$$

Time Series Momentum

One of the most ubiquitous measure of time series momentum is based on asset returns over the preceding 12 months, in excess of a risk-free rate. When the excess holding period returns are positive, this may signal that the analyzed asset prices are trending upward. Similarly, when the excess holding period returns are zero or negative, this may indicate either a lack of trend in asset prices or a downward trend.

Mathematically and abstracted to a generalized lookback period of size k, measures of time series momentum can be expressed as follows:

$$TSMOM_t^k = r_{\{t-k,t\}} - rf_{\{t-k,t\}}$$

where

$$r_{\{t-k,t\}} = \text{Returns on asset earned from time t-k to t}$$
$$rf_{\{t-k,t\}} = \text{Risk-free rate earned from time t-k to t}$$

We analyze three separate look-back periods to compute corresponding measures of time series momentum. Specifically, we compute measures of momentum based on values for k that correspond to 1-month, 3-months, and 12-month look-back intervals. These are utilized to compute a composite measure of time series momentum that is a weighted combination of the three individual measures. The use of three look-back periods is considered to be a more

robust measurement of time series momentum. Moskowitz (2012) shows that the t-stat for the alpha (controlled for exposure to the stock market, bond market, commodity market as well as the Fama-French factors) generated from TSMOM strategies are significantly positive for holding periods of 1 up to 12 months. Our composite measure is computed as follows:

$$TSMOM_t = \sum TSMOM_t^k * w_k$$

where

$$w = [12.5\%,\ 37.5\%,\ 50.0\%] \text{ for k} = 21,\ 63,\ 252 \text{ trading days respectively}$$

This composite measure can then be translated into a binary signal to correspond to suggested trades. We convert the time series momentum measure into binary form where a value of 0 suggests no deviation should be made from the existing position, and a value of 1 suggests that some portion of the position in the risky asset should be shifted to the risk-free asset:

$$TSMOM_t^b = \begin{cases} 0 \ : \ TSMOM_t \geq 0 \\ 1 \ : \ TSMOM_t < 0 \end{cases}$$

Simple Moving Average

Moving average crossovers detect when current asset prices levels pass through a threshold defined by a moving average of past prices. Theoretically, breaking through the threshold may be viewed as a signal that prices will continue to trend in that direction for a period of time. We compute a simple moving average crossover signal by comparing current asset prices to their moving average of prices of the past 252 trading days as follows:

$$SMA_t^k = P_t - \frac{1}{k}\sum_{i=t-(k+1)}^{t-1} P_i$$

where

$$k = 252 \text{ trading days}$$

As with the time series momentum signal discussed above, here too we convert the simple moving average crossover measure into a binary signal that can inform suggested trades. Once again, a binary signal value of 0 indicates no change to the existing position in the risky asset, and a value of 1 suggests some portion of the position in the risky asset should be shifted to the risk-free asset:

$$SMA_t^b = \begin{cases} 0 \ : \ SMA_t^k \geq 0 \\ 1 \ : \ SMA_t^k < 0 \end{cases}$$

Composite Signal

A composite signal is computed based on observed values for each of the three binary signals discussed above. The amount of the position in an individual asset that should be shifted to the risk-free asset at time t is determined based on the number of signals observed as equal to 1 at that time.

The total number of signals considered varies according to asset type. The absorption ratio is only computed for assets where time series data on underlyings for the investable asset is readily available and the correlation structure of those underlyings is expected to have measurable variation over time. In this analysis, we analyze the absorption ratio for all equity indices. For all equity and non-equity assets, the time series momentum and simple moving average crossover signals are computed.

The composite signal C_t is computed as follows:

$$C_t = \sum_{i=1}^{j} S_t^i$$

where

$$C_t = \text{Composite signal at time t}$$
$$S_t^i = \text{Binary signal } i \text{ at time t}$$
$$j = \text{Maximum number of binary signals}$$
$$j = 2, 3 \text{ for non-equity and equity assets, respectively}$$

Shifts to the risk-free asset are inferred based on the time series of the composite signal for the analyzed asset. These shifts are defined as follows:

For $j = 2$:

$$Shift_t = \begin{cases} 0.00 & \vdots\ C_t = 0 \\ 0.50 & \vdots\ C_t = 1 \\ 1.00 & \vdots\ C_t = 2 \end{cases}$$

For $j = 3$:

$$Shift_t = \begin{cases} 0.00 & \vdots\ C_t = 0 \\ 0.25 & \vdots\ C_t = 1 \\ 0.50 & \vdots\ C_t = 2 \\ 1.00 & \vdots\ C_t = 3 \end{cases}$$