Ride on the Interest Rate Hike: Asset Allocation in a Recovering Economy

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1 Introduction

Interest rates may well constitute the single most important risk factor in the investment world as virtually all asset class valuation models include the risk-free rate. Looking at the current macro-environment of low unemployment rates and moderate inflation, the Fed expects a gradual increase in the Fed Funds Rate[14]. This provides a supportive base for further tightening for the rest of 2017. In this paper, we put ourselves in the shoes of a sophisticated long-term asset manager to critically and thoroughly examine the effects of an interest rate hike on equities, bonds, commodities and currencies and their correlations. We propose a tactical portfolio for the sophisticated asset manager to hold in 2017. Moreover, we further examine the effects of a hike within these asset classes.

1.1 Inflation vs Growth-driven Hikes

According to the Fed's dual mandate - "maximizing employment and stabilizing prices"[15], interest rate hikes can occur for two reasons. During a period of unexpected high inflation, the Fed could restrict the money supply to rein back an overheated economy. Alternatively, when the economy is rising from a trough, the Fed could raise interest rates from an artificially low level so that the expected growth is sustainable. In the first case the hike is inflation-driven while in the second it is growth-driven. Depending on the cause of the hike, we would expect asset classes to behave differently.

Two energy crisis in the 1970s led to an increase in oil prices and hindered US growth. To counter this, the Fed increased money supply to manage aggregate demand and control the unemployment rate at the cost of inflation. As the economy was close to its maximum level of output, further expansionary push led to inflation with minimal reduction in unemployment rates. This led to a dismal economic state in the US which was the main driving factor behind the hikes.[16] On the other hand, the 1994/2004 hikes were a response to substantial improvements in labor markets. According to Greenspan[17], the Fed's intent was to target long -term equilibrium rates, as higher rates could lead to disinflation and economic stagnation while lower rates could cause inflation.

Our strategy is to relate the behavior of each asset class from past hikes that occurred in similar environments to the current hike, from which we form our views on regime-specific returns and correlations to build a tactical asset allocation. As discussed earlier, we believe that the latest and the expected hikes are growth-driven. We thus identify each growth-driven hike in history and add them to our learning sample.

1.2 Hike Detection and Classification

It is often hard to determine the start and end of a tightening period precisely. For example, some hikes ceased after a short period (less than 6 months). These are most likely short-term deviations from equilibrium rather than the Fed's persistent discretionary response to the economic cycle.

More recently, the unprecedented quantitative easing (QE), which has strongly affected the economy, was not captured in the constant near-zero Fed Funds Rate. To translate QE's impact into Fed Funds Rate policy, we obtain the Atlanta Fed's Wu-Xia Shadow Federal Funds Rate(SR)[1] and compare it with the St. Louis Fed's Effective Federal Funds Rate (ER) [12]. Unlike the ER, the SR, which was available after global financial crisis to take into account the full effects of QE, does not have a lower bound at zero. The SR changes continuously to reflect the concurrent money supply. We found that the latest tightening cycle did not start in 2015 when the Fed increased the Fed Funds rate, but in 2014 when the Fed began tapering its portfolio of bonds to reverse the effect of QE. We used the SR from Dec 2009 to Dec 2016 and the ER for the rest of time for interest rate hike detection.

To avoid detecting spurious hikes, we smoothed out the rate curve (ER and SR) using a 12-month moving average. We determined the start and end of Fed tightening cycle by detecting troughs and peaks of the curve.

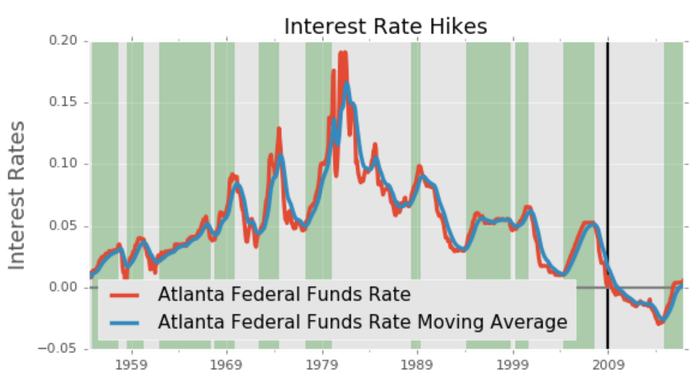

Figure 1: Interest rate hikes

To classify a hike, we looked at inflation, the unemployment rate and GDP growth at the beginning and during each tightening cycle. A growth-driven hike usually has low inflation at the beginning that remains low during the hike period. Also, the unemployment rate usually decreases while GDP growth generally accelerates during the hike period. On the other hand, an inflation-driven hike usually starts with high inflation. Further increases in inflation and the unemployment rate are expected during such periods. GDP growth generally remains weak or worsens during the hike. Moreover, since the Fed's reaction to unexpected inflation is usually aggressive, a growth-driven hike is usually gradual and lasts longer than an inflation-driven hike.

Figure 2 summarizes the different macro environments of each hike and their classifications as inflation-driven and growth-driven. In addition, we exclude the growth hike from May 1999 to August 2000 because of the over-priced market which crashed one year later. The Shiller's CAPE at May 1999 was over 40 which indicates that equity was over-valued, whereas now the Shiller's CAPE is about 25 [24]. Therefore, we believe the macro environment of the dot com bubble does not resemble the current economic state.

1.3 Optimal Allocation Strategy

We recognize that there are not many growth-driven hikes in history. We are therefore careful to design an allocation process that is not overly driven by past data. We aim to create a process that is intuitive, robust and that captures as much information as possible. With so few hike periods to learn from, forecasting expected returns becomes a hard task. Also, for a profit seeking investor, it is more important to relatively rank the assets rather than accurately forecast individual asset returns[18]. In this paper, we generate ordinal views on asset class performance by studying historical growth hikes. We then introduce a method that converts these ordinal views into alphas (expected active returns) conditioned on the variance-covariance matrix of asset classes and a reasonable expected information ratio (IR). We use a Regime Switching Multivariate GARCH model (see Section 3.3) to forecast the variance-covariance matrix for the expected hike. The model allows us to use the entire history of returns, but still make separate forecasts for different anticipated regimes. With the active views and the risk model, we construct a tactical portfolio relative to the market cap weighted portfolio through the Black-Litterman framework. The size of our tactical bets depends on our confidence level on our views.

2 Data

Asset Classes: We use the monthly total returns of the US Stock Index, US 10 Year Government Bond Index, S&P Goldman Sachs Commodity Index, Gold Bullion Price, US Dollar Real Effective Exchange Rate from the Global Financial Data database [19], and Merrill Lynch High Yield Bond Index from St Louis FRED [12]as our proxies for equity, government bonds, commodities, gold, US dollar and high yield bond respectively. We use the relative market weights for each asset class from the global investment proportion based on a report prepared by Aon-Hewitt [20]. We only used data after 1971, the termination of Dollar-Gold pegging, for studies that involves gold.

Equities and Bonds: We use US S&P 500 sector total

Start	Nov-54	Aug-58	Dec-61	Oct-67	May-72	May-77	May-88	Mar-94	May-99	May-04	Dec-14
End	Jul-57	Mar-60	Apr-67	Oct-69	May-74	Dec-79	Apr-89	Sep-98	Aug-00	Jun-07	Ongoing
Length (month)	32	19	64	24	24	31	11	54	15	37	Ongoing
SR at the start of hike	0.8%	1.5%	2.3%	3.9%	4.3%	5.4%	7.1%	3.3%	4.7%	1.0%	-2.42%
SR at the end of the hike	3.0%	3.8%	4.1%	9.0%	11.3%	13.8%	9.8%	5.5%	6.5%	5.3%	0.54%
Total Rate Change	2.2%	2.3%	1.7%	5.1%	7.0%	8.4%	2.8%	2.2%	1.8%	4.3%	2.96%
Inflation at the Start	0.0%	2.3%	1.0%	2.9%	3.7%	6.6%	3.6%	2.8%	2.1%	2.5%	0.78%
unemployment at the Start	5.3%	7.4%	6.0%	4.0%	5.7%	7.0%	5.6%	6.5%	4.2%	5.6%	5.6%
GDP Growth at the Start	-0.6%	-0.7%	2.6%	2.7%	5.3%	4.6%	4.2%	4.0%	4.7%	3.8%	2.4%
Change of Inflation/year	1.0%	-0.6%	0.3%	1.1%	2.4%	1.6%	1.0%	-0.2%	0.6%	0.2%	Ongoing
Change of unemployment/year	-0.4%	-1.3%	-0.4%	-0.2%	-0.3%	-0.4%	-0.4%	-0.4%	-0.1%	-0.3%	Ongoing
Change of GDP Growth/year	1.0%	2.1%	0.0%	0.2%	-2.9%	-0.6%	-0.6%	0.1%	-0.5%	-0.7%	Ongoing
Classification	Growth	Growth	Growth	Growth	Inflation	Inflation	Inflation	Growth	Bubble	Growth	Growth

Figure 2: Macro Environment for Detected Interest Rate Hikes

returns (Financials, Health Care, Energy, Information Technology, Consumer Discretionary, Consumer Staples, Industrials, Utilities, Telecommunication and Materials) from Bloomberg as proxies for equity sectors. We use the MSCI Emerging Market Index and the FTSE Developed Market Ex US Index as proxies for Emerging Market (EM) stocks and Developed Market (DM) stocks respectively. Size, Value and Momentum style factor portfolio returns are obtained from the Kenneth R. French Data Library. The one to thirty-year zero rate term structure is sourced from US Federal Reserve Data Releases. We obtained the BofA Merrill Lynch US Corporate credit option adjusted spread data for rating AAA to C from St. Louis Fed. The relative market weights of the equity sub-class is determined based on the study by Siblis Research [2].

3 Methodology

3.1 Performance Ranking

We rank the cumulative returns of the asset classes and the sub-classes over the two-year period from the start of a growth hike. Since we have a small sample of 11 historical hikes, we qualitatively distinguish the macro-economic conditions that are different from the current regime. To form a view, we look for consistency in rankings across all past growth-driven hikes as well as qualitative arguments regarding the current regime. For example, if stocks were the best performing asset historically, then we have high confidence that stocks are going to outperform others during the expected hike period. Similarly, if government bonds had the worst performance historically then its rank forecast in the next period will be the lowest. These ranking forecasts are used to generate active bets in 3.2.

3.2 Rankings Converted to Active Bets

We introduce a method to generate views (alphas) given performance rankings, volatilities and correlations of asset classes, as well as an expected Information Ratio. Almgren and Chris (2004) [5] provided proof that an optimal portfolio based on ranking information could be constructed by solving the following linear programming problem:

$$\begin{aligned} \max_{\omega} \quad & c^T \omega \\ \text{s.t.} \quad & \omega^T \Sigma \omega \leq \sigma^2 \end{aligned} \tag{1}$$

where ω are portfolio weights, Σ is the variance covariance matrix and c is the centroid vector of the cone spanned by the ranking constraints in the return vector space. Intuitively, the cone stands for the feasible set of alpha vectors under the ranking constraint ($r_1 > r_2 > r_3 \ldots$), where the optimal direction of alphas is along the centroid vector of the cone. However, setting alpha equal to c does not guarantee a realistic IR. Grinold and Kahn [6] proposed to scale alphas based on an expected ex ante IR. By incorporating the direction of the active views (from the centroid vector c), a measure of uncertainty in the asset returns (from the covariance matrix) and an estimate of our information ratio (e.g. 0.5), we derive the alphas as:

$$\begin{aligned} IR_{rank} &= \sqrt{c^T \Sigma^{-1} c} \\ \alpha &= \frac{IR_{ex-ante}}{IR_{rank}} \cdot c \end{aligned} \tag{2}$$

Note in the above formulation, the magnitude of c does not matter as it is ultimately controlled by the ex ante IR.

3.3 Regime Switching Multivariate GARCH

We expect the covariance matrix to vary depending on the market regime (see Section 4.2) and propose a Regime-Switching Multivariate GARCH (RSM-GARCH) [8] [9] model to estimate the variance-covariance matrix of asset classes (or sub-classes):

$$R_t^{(i)} = \alpha_{k_t}^{(i)} + \beta^{(i)} R_{t-1}^{(i)} + \gamma_{k_t}^{(i)} r_t + \epsilon_t^{(i)} \tag{3}$$

$$\vec{\epsilon_t} \sim \mathcal{N}(0,\ \Sigma_t) \tag{4}$$

$$\Sigma_t^{(i,j)} = \mu_{k_t}^{(i,j)} + \phi^{(i,j)} \epsilon_{t-1}^{(i)} \epsilon_{t-1}^{(j)} + \psi^{(i,j)} \Sigma_{t-1}^{(i,j)} + \theta_{k_t}^{(i,j)} r_t \tag{5}$$

Where $R_t^{(i)}$ is the monthly return of index i. r_t is the monthly SR, $\Sigma_t^{(i,j)}$ is the covariance between asset classes i and j, $\epsilon_t^{(i)}$ is the shock term, and k_t is the regime indicator. In our model, there are three types of regimes: 1. A non-tightening regime, 2. A growth-driven tightening regime, 3. An inflation-driven tightening regime. For each type of regime, we assume distinct level effects for both return and covariance[21], represented by $\alpha_{k_t}^i$ and $\mu_{k_t}^i$ respectively. We also assume that the short term interest rate has distinct effects on return and covariance, represented by $\gamma_{k_t}^i$ and $\theta_{k_t}^i$ respectively. Unlike some regime-switching models in which regime identification is endogenous [8], in our model, regimes are exogenously pre-identified through evaluating macro environment variables (see Section 1.2). The exogeneity allows the model to incorporate more information, to ensure robustness and to simplify estimation. We finally assume that the autoregressive dynamic of return and covariance are independent of regimes, thus giving a constant $\beta^{(i)}$, $\phi^{(i,j)}$ and $\psi^{(i,j)}$. We used pairwise bootstrapping [10] in the Maximum Likelihood Estimation of Multivariate GARCH: each time we picked a pair of assets and estimated the corresponding parameters. This procedure gives one off-diagonal covariance forecast. Then we used univariate Regime-Switching GARCH to estimate the diagonal variance. To ensure that the variance-covariance matrices are positive semi-definite (PSD), we used the absolute eigenvalue matrix for non-PSD correction and diagonal ridging for singular correction.

3.4 Black-Litterman Asset Allocation

The Black Litterman Model [7] allows investors to express their views (e.g alphas from rankings) on top of the equilibrium asset returns implied by market capitalization. In our implementation, the active allocation is achieved in four steps:

1). Derive the implied asset returns Π_{eq} from CAPM equilibrium (Reverse optimization):

$$\Pi_{eq} = \delta \Sigma \omega \tag{6}$$

where δ is market risk aversion coefficient estimated from the historical Sharpe ratio of the market portfolio. Σ is the covariance matrix estimated from RSM-GARCH model. ω is the current market capitalization.
2). Update the implied returns Q with investor's views by adding alphas (see section 3.2):

$$Q = \Pi_{eq} + \alpha \tag{7}$$

where, Q is the updated view returns.

3). Calculate the posterior expected returns and update the covariance matrix with the additional uncertainty introduced by the views:

$$\mathbb{E}(R) = [(\tau\Sigma)^{-1} + P^T \Omega^{-1} P]^{-1} [(\tau\Sigma)^{-1} \Pi_{eq} + P^T \Omega^{-1} Q]$$

$$\Sigma_{new} = [(\tau\Sigma)^{-1} + P^T \Omega^{-1} P]^{-1} + \Sigma \tag{8}$$

where P is the identity view matrix corresponding to each row of Q. The view is expressed at each individual asset level. Ω is a diagonal matrix with the uncertainty of each view on the diagonal. We used the framework from He and Litterman(1999) [13]: $\Omega_{ii} = \tau \sigma_{ii}^2$. τ describes the uncertainty and estimation error in CAPM equilibrium returns. We used τ = 0.05 in this study and the results are not sensitive to τ.
4). Generate the asset weights for each frontier portfolio through Markowitz Mean-Variance optimization given the posterior expected returns and covariance matrix by running the following quadratic optimization problem with different values of λ:

$$\begin{aligned} \max_{\omega} \quad & \mathbb{E}(R)^T \omega - \lambda \omega^T \Sigma_{new} \omega \\ \text{s.t.} \quad & \sum_{i=1}^{n} \omega_i = 1 \\ & w_i \geq 0 \, \forall i \in N \end{aligned} \tag{9}$$

The final allocation incorporates both market information and private views. It is robust, forward-looking, and mean-variance optimal.

3.5 Term Structure Forecast

We provide a framework of asset allocation within the fixed-income class, based on the principal components[PCs] analysis of term structure. We show in Figure 3 that the zero rate term structure can be decomposed into three PCs–level, slope and curvature, which explain 95.9%, 3.8%, 0.1% of total variation respectively according to our calculation. We believe, for long term asset allocation, conducting PCA on the interest rate themselves (level values) is more appropriate than on the change of rates. The PCA on interest rate changes was first introduced by Litterman and Scheinkman[11]. Our goal is to forecast the change of the shape of term structure over a long period of time, instead of hedging or predicting interest movement over a week or a month. With PCA on level, we can directly observe the evolution of term structure summarized by its three components over a long horizon. This approach has been previously adopted for option pricing [22].

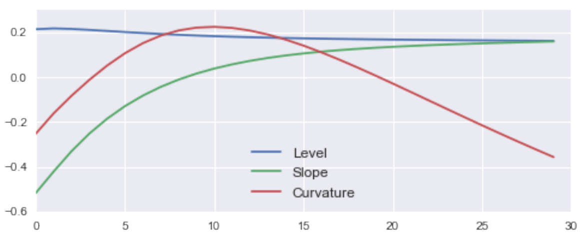

Figure 3: Loading of principle components

At a given time point t, the three PCs give us a good approximation $\tilde{r}_{0,T}$ of zero rate $r_{0,T}$ with maturity T as follows:

$$\tilde{r}^{0,T}(t) = w_1^{(T)} PC_1(t) + w_2^{(T)} PC_2(t) + w_3^{(T)} PC_3(t), \tag{10}$$

We defined an approximated discount factor $D_{0,T} \approx D(\tilde{r}_{0,T}, T)$, which depends on compounding. For any bond with predefined coupons, its price is the sum of discounted cash flows:

$$\begin{aligned} P &= \sum_{T \in \{T1, T2..T_N\}} C_T D_{0,T} \approx \sum_{T \in \{T1, T2..T_N\}} C_T D(\tilde{r}_{0,T}, T) \\ &= f(PC_1, PC_2, PC_3) \end{aligned} \tag{11}$$

At a given time, $w_i^{(T)}$, PCs, discount functions and coupons are known for a bond. As f is a known function for the bond, we can derive the sensitivity of its price to the PCs through stress testing with a small shock δ as follows:

$$\beta_1 = \frac{1}{\delta}\left(f(PC_1 + \delta, PC_2, PC_3) - f(PC_1, PC_2, PC_3)\right)$$

We obtain β_2 and β_3 similarly. We approximate the change of the bond price as follow:

$$\Delta P \approx \beta_1 \Delta PC_1 + \beta_2 \Delta PC_2 + \beta_3 \Delta PC_3 \tag{12}$$

Once we have a prediction for the change in the PCs, we can derive the expected return of each bond and thereby the ranking of each bond used by our optimizer. We also derive the factor based covariance matrix $\boldsymbol{\beta}^T \cdot \boldsymbol{V} \cdot \boldsymbol{\beta}$, where $\boldsymbol{V}$ is the covariance matrix of the principle components and the i^{th} column of $\boldsymbol{\beta}$ represents PC sensitivities for the i^{th} bond.

4 Asset Class Allocation

4.1 Event Study Results

We examine the behavior of the asset classes for each hike period and notice remarkably similar behavior across the growth-driven hike periods. Figure 4 summarizes the relative performance of the asset classes in each individual hike period. Figure 5 summarizes the performance of each asset class across these periods. Before 1972, we only have data for stocks and government bonds. We notice that stocks consistently outperform bonds during all growth-driven hike periods. The hikes during the 1970s and 1980s are primarily inflation-driven during which commodities outperform all other assets and the US dollar fell. From 1994 to present, we only experienced growth-driven hikes. The median ranking across the growth-driven hikes is as follows:

1. US Equity
2. Commodity
3. US High Yield Bond
4. US Government Bond
5. Gold
6. US Dollar

Hike Start date	US G. Bonds	US Stocks	US Dollar	Gold	Commodities	HY Bonds
1954-11	2	1	NaN	NaN	NaN	NaN
1958-08	2	1	NaN	NaN	NaN	NaN
1961-12	2	1	NaN	NaN	NaN	NaN
1967-10	2	1	3	NaN	NaN	NaN
1972-05	2	3	4	NaN	1	NaN
1977-05	4	3	5	1	2	NaN
1988-05	3	2	5	6	1	4
1994-03	4	1	5	6	2	3
1999-05	3	2	4	5	1	6
2004-05	5	3	6	1	2	4
2014-12	4	1	2	5	6	3
Hike Type	**Median Rankings After 1972**					
growth	4	1.5	4.5	5	2	3.5
inflation	3	3	5	3.5	1	4

Figure 4: Cross-sectional performances ranking.

The historical rankings give us an idea on how the asset classes performed relatively to each other in the past. To form a forward-looking view, we discuss each asset class' past behavior during growth-driven hike periods and the expected performance for the expected hike.

Equity: Stimulated by a rapidly expanding economy, the US Stock market has historically shown substantial returns during growth-driven interest rate hike periods. The US equity drawdown during the start of 1961 hike stands as the only exception. This can be attributed to the uncertainty caused by the Bay of Pigs attack of April 1961 and the Cuban Missile Crisis of October 1962. However, the market recovered after the initial shock. On average the stock market went up by 25% in the 2 years after the start of interest rate hike.

Government Bond: Historically, the ten-year treasury bond experienced moderate price changes after the tightenings. During growth-driven hikes, the long term yield increases at a slower rate than the short-term yield, resulting in term spread tightening. On average, the 10-year bond has shown better performance in hikes post 1981, as the trend of 10-year rate is upward sloping before 1981 and downward sloping post 1981. For the expected hike, we think that three factors could go against Treasury instruments: higher short term rates, higher inflation risk premium as the economy picks up and the Fed's action to begin selling long-term assets from its balance sheet.

High Yield Bond: High yield bonds incorporate both an interest rate risk premium and a credit risk premium, with the latter exposed to economic growth. Under a growth-driven environment, new and financially weak firms have larger growth potential, smaller default probability and thus lower cost of capital. The high yield bonds rally in these periods as the interest rates may rise gradually but the credit spread often narrows more dramatically. Our view is that credit spread will continue to narrow in 2017.

Commodities: Commodities have rallied during both inflation-driven and growth-driven hikes. During growth hikes, increasing aggregated consumption and industrial output drove up the demand for materials and fuel, pushing up their prices. Although commodities crashed in 2015 due to oil oversupply and a growth slowdown in emerging markets, their prices have gradually picked up from there. The growth potential is still large considering the current phase of economy. Overall, commodities showed an upward sloping trend at high volatility. The demand for commodities as an inflation hedging tool also increases as moderate inflation is expected during economic growth.

Gold: Gold is typically considered as a safe haven. The strongest gold rallies were generally observed during financial downturns and not during economic growth periods. However, considering the uncertainty of Trump's political and economic policies and their broader implications, as well as the spreading of populism over the pending European elections, we view gold as a valuable hedge and thus increase its ranking.

The US Dollar: The US dollar's performance depends on the macro environment and policies of other economies. If the US is the only economy raising interest rates then the US dollar should strengthen. This is what we observe for the current hike. However, during the two historical growth hikes, the US dollar stayed relatively flat due to other economies also raising interest rates. Also, currently the US dollar is valued at a fairly high level, and we feel that the recent rally may not continue if other economies strengthen and raise interest rates in 2017.

In conclusion, based on the above analysis, our ranking is as follows:

1. US Equity
2. Commodity
3. US High Yield Bond
4. Gold
5. US Dollar
6. US Government Bond

4.2 Volatility and Correlation forecasts

We investigated the historical volatilities (annualized) and correlations of monthly asset returns during non-tightening periods, growth-driven tightening and inflation-driven tightening periods. Figure 6 shows the heat maps of the correlations. For the first two regimes, we found low correlation between stocks and government bonds and high positive correlation between stocks and high yield bonds. The US dollar has negative correlation with all other assets, except government bonds. This could result from the scenario when the global market was performing poorly including the US market, and investor chose US dollar and Treasury instruments as a safe haven to avoid taking other risks. Commodities had negative correlations with government bonds and US Dollar, and positive correlations with gold and high yield bonds. During the inflation-driven tightening periods, we found positive correlations among stock, government bond and US dollar, which were negatively correlated with commodities and gold.

Figure 7 shows the heat maps of the forecast volatilities and correlations of monthly asset returns for the pending growth-driven tightening period (estimated at Jan 1, 2017) estimated by Exponential Weighted pairwise Covariance (EWCOV) and RSM-GARCH. We also present the 1-year tailing historical volatilities and correlations. We found that US stocks, commodities and high yield bonds are positively correlated to each other and generally negatively correlated with government bonds, the US dollar and gold. The only exception is: the forecast predicts slightly positive correlation between gold and commodities. We also found that government bonds and gold are highly positive correlated. Overall, the correlation estimated from RSM-GARCH is more conservative than that estimated from EWCOV.

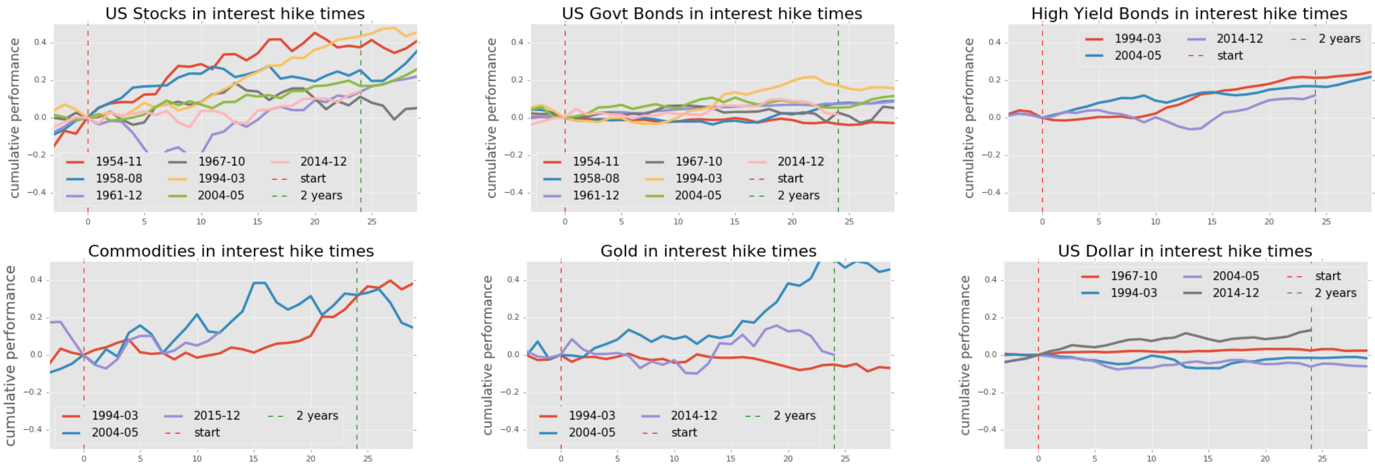

Figure 5: Performance of the six assets during historical growth-driven interest rate hike.

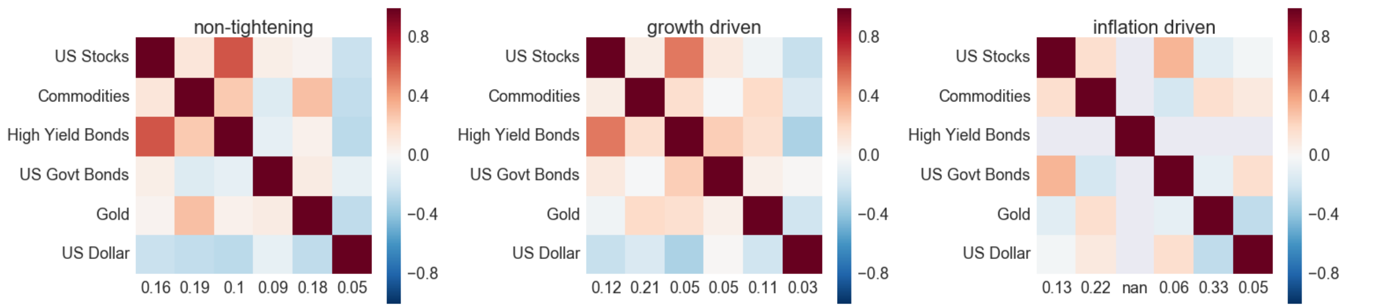

Figure 6: Historical correlation matrix and annualized volatility displayed in x-label: **Left:** non-tightening period, **Middle:** growth-driven interest rate hike, **Right:** inflation driven interest rate hike. historical high yield bond index is not available in inflation driven hike

The most recent historical and predicted correlations are consistent with our asset performance rankings.

Since asset allocation is sensitive to covariance estimation, we compared the RSM-GARCH fitted covariance with that from EWCOV over time. We illustrate four pairs in Figure 8. In general, the RSM-GARCH fitted covariance is more stable than that from EWCOV. We observed regime switching effects in some pairs such as Stocks-Stocks (left) and Stocks-High Yield Bonds (middle) and US Govt Bonds-US Dollar (right), where the covariance was levered up and down when entering a new regime.

4.3 Broad Asset Class Allocation

Assuming the next year's broad asset class performances follow the ranks obtained in Section 4.1. The adjusted alphas after shrinking the information ratio to 0.5 is -2.54%, 2.54%, -1.28%, -0.40%, 1.28%, 0.40%, for Government Bonds, Equities, US Dollar, Gold, Commodities and High Yield Bonds respectively. Consistent with the rankings, we see positive alphas for US stocks, commodities and high yield bonds, as we expect them to beat the market's expectations implied by the equilibrium.

The upper left chart in Figure 9 shows the difference between the market implied expected returns and the Black-Litterman expected returns after incorporating the views. The posterior returns shift in the same directions suggested by the relative strength of each asset performance during growth-driven tightening periods.

With the updated expected returns, we computed the asset allocation through mean-variance portfolio optimization. In Figure 9, the lower left chart shows the efficient frontier whereas the lower right chart illustrated the change of asset composition when moving along the frontier. As the investor becomes less risk adverse (equivalent to increasing the target portfolio volatility), the allocation tilts towards stocks. In the opposite direction, the investor allocates more in the US dollar as it is negative correlated with all other assets in either the forecast or history of growth-driven tightening periods.

The upper right chart in Figure 9 illustrates the optimal allocation at the same volatility of the market portfolio. The asset allocation deviates from the market and tilts towards US stocks, commodities, high yield bonds, US dollar and gold. The only asset down-weighted is the government bond. The first three assets are those we believe will rally under the rising interest rate environment. The optimizer only slightly over-weighs stocks as its proportion is already high in the market portfolio and it does not provide much diversification benefit. Instead, the optimizer favors high yield bonds as an alternative. Due to hedging benefits, US dollar and gold

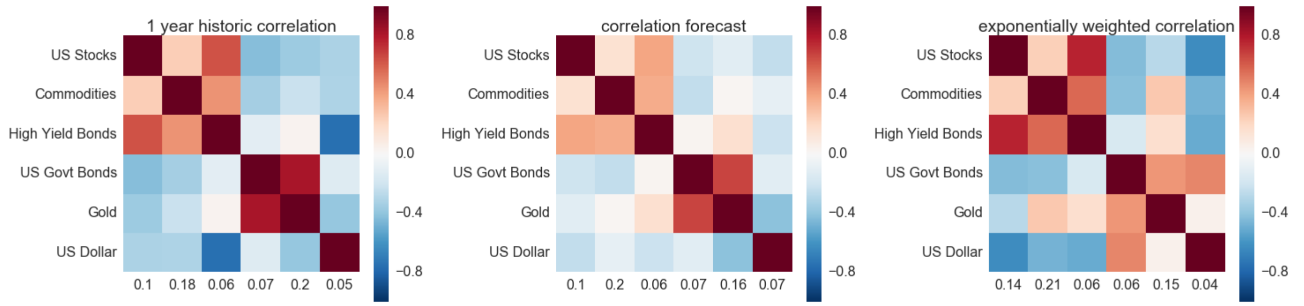

Figure 7: Correlation and volatility displayed in x-label by GARCH forecast and benchmarks: **Left:** 1 year trailing historic correlation, **Middle:** RSM-GARCH forecast, **Right:** exponentially weighted historic correlation

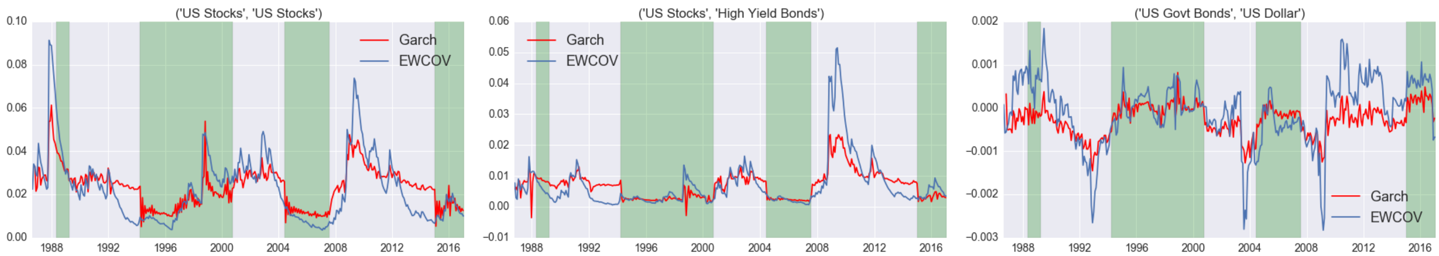

Figure 8: GARCH fitted Covariance time series in past 30 years in comparison with EWCOV (halflife=6)

are also over-weighted, especially for US dollar.

5 Sub-Class Allocation

5.1 Equity Market

5.1.1 Style analysis

We conducted a ranking analysis for Size, Value and Momentum factors in Carhart's four factor model[23] to further allocate across instruments within the US equity class:

- **Relative level analysis:** We obtained the average return during each growth-driven hike period and 5-year historical average return at the start of the hike for each style factor. We used the ratio of the first return to the second return to rank the style factors for their sensitivity to the hike. The higher the ratio, the better the ranking.

- **Absolute level analysis:** We compared the actual average returns achieved during the hike periods to rank the style factors.

The performance rankings is summarized in Table 1.

Hikes	Relative (Absolute) Rankings		
	Value	Size	Momentum
1954-57	1 (2)	3 (3)	2 (1)
1961-69	1 (3)	2 (2)	3 (1)
1994-00	3 (2)	2 (3)	1 (1)
2004-07	1 (1)	3 (3)	2 (2)
2014-Present	1 (1)	2 (2)	3 (3)
Overall	1 (2)	3 (3)	2 (1)

Table 1: Style Rankings at relative and absolute level where figures in paranthesis represent absolute rankings

According to the relative rankings, value works best, followed by size and momentum. According to the absolute level rankings, momentum works best, followed by the value and size. We also observed that momentum has not been working well over the last year. Historically, as the drawdown in momentum factor does not persist for a long period (9 months on average). We have confidence in the momentum factor reviving in the next period. We conclude that during the growth-driven hike periods, momentum performs be followed by the value and size factors.

5.1.2 Sector Strategies

To allocate weights within the equity sectors, we conduct a relative ranking analysis across cyclical, defensive and sensitive sectors following the event study methodology discussed in Section 3. Based on this analysis, we observe that even though all the sectors performed well during the recent growth-driven tightening periods(1994/2004), there are no clear relative rankings across the sectors.

Our findings are contrary to the traditional wisdom

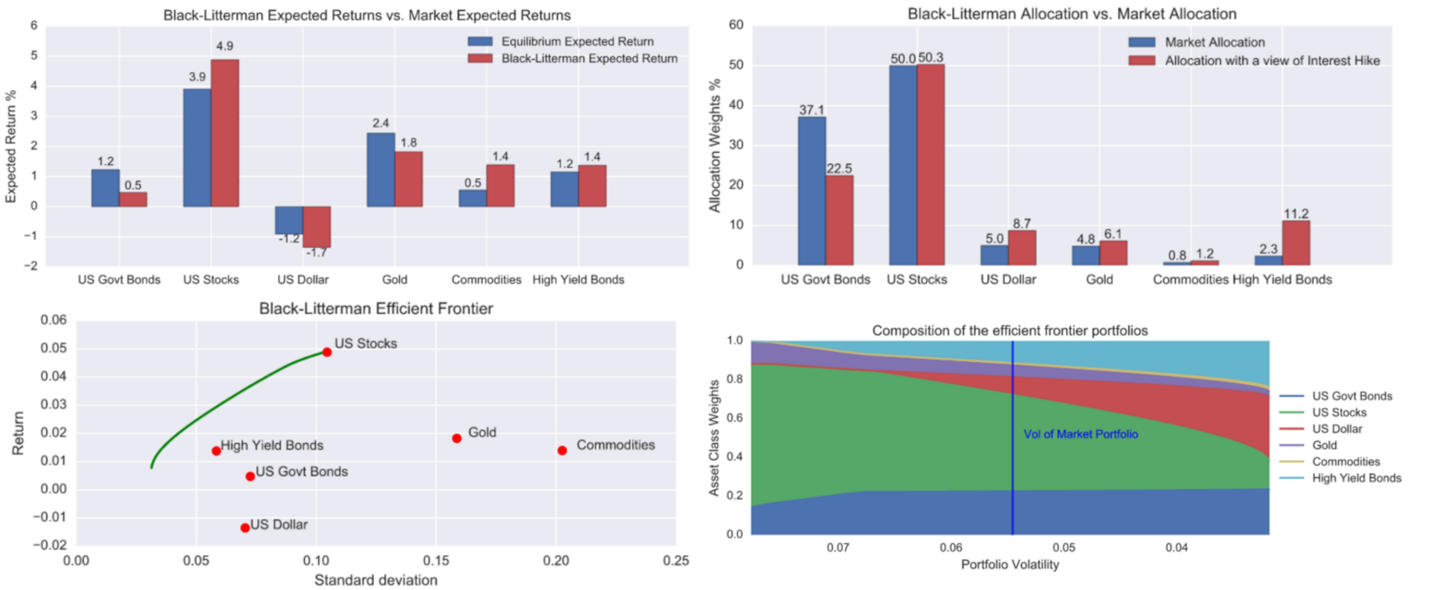

Figure 9: Black-Litterman asset class allocation. **Upper left:** Prior and posterior expected returns, **Upper right:** Allocation comparison using market volatility**Lower left:** Efficient frontier,**Lower right:** Frontier portfolio positions

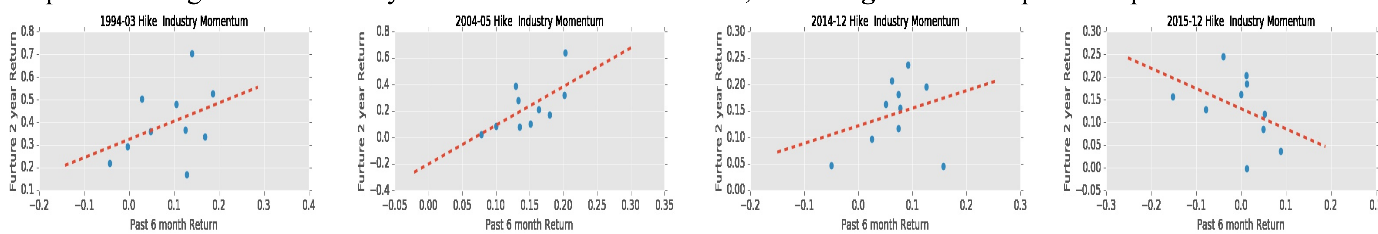

Figure 10: Momentum Effect: Past 6 month Return and Future 2 year Return

that Financials and Utilities underperform while industrials outperforms during interest rate hikes. In fact, Utilities returns increased sharply in the 2004 hike and the Financials sector performed well in 1994. Also, Industrials ranked middle in both the hikes. We believe the underlying reason for not obtaining a consistent ranking is the dependence of sectors on many diverse factors such as technology development, regulations, and emerging market economic outlook . Thus, we conclude that the growth-driven interest rate hike shock has a marginal effect on distinguishing sectors performance.

As cumulative returns failed to give consistent rankings across sectors, we evaluated the performance of a sector momentum strategy during these hike periods. Figure 10 demonstrates the relationship between historical 6 month return and future 2 year return of different sectors. Historically, there was a positive relationship between past and future industry return after growth-driven interest rate hikes. However, 2015 saw a crash in the sector momentum strategy. As momentum strategies tend to rebound after a crash, a recent crash may imply a good investment opportunity for sector momentum.

Using the same Black-Litterman technique, Figure 11 shows the optimal allocation within US equity based on a ranking of recent sector momentum. The healthcare sector, with a low rank, has a negligible allocation. In achieving the same annualized volatility of 9.5% as the equity sector, the Financials, IT, Industrials, Utilities and Material sectors are over-weight, which is sensible in light of the future growth in the economy and hence the positive outlook for stable Financial and IT sectors as well as sustainable industrial growth.

We further looked at the relative performance of cyclical stocks vs defensive stocks. According to the definition from Morningstar[25], cyclical stocks comprise of Basic Materials, Consumer Cyclical, Financial Services and Real Estate sectors; defensive stocks comprise of Consumer Defensive, Healthcare and Utilities sectors; sensitive stocks comprise of Communication Services, Energy, Industrials and Technology sectors. We created an equal weight sector index for each category. As per Table 2 the sensitive sectors perform relatively well during the tightening periods. We believe that the ranking results (Sensitive > Cyclical > Defensive) are in with our expectations of a strong economy during a growth-driven interest rate hike.

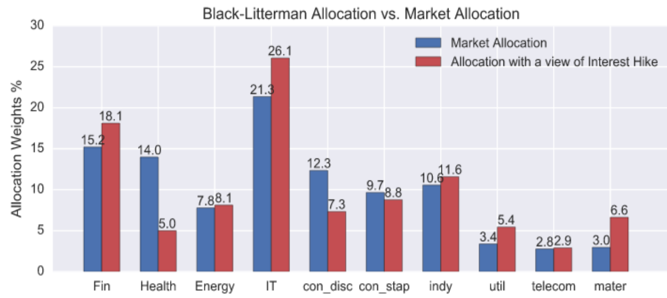

Figure 11: Equity Market Sector Allocation

	Sector			Global		
	cyclical	defensive	sensitive	EM	DM	US
1994-03	3	1	2	3	2	1
2004-05	2	3	1	1	2	3
2014-12	2	3	1	3	2	1
2015-12	2	3	1	2	3	1

Table 2: Ranking of Sector and Global Equity during historical growth-drive interest rate hikes

5.1.3 Global Equities

As per Table2, we find no evidence supporting the view that EM and Non-US developed markets outperformed US stock market during the past US Fed tightening cycles. Although we cannot rank emerging markets and non-US developed markets relative to US stock markets, we believe that effect of interest rates on commodities can capture the indirect effect of a hike on international equities. As we expect commodities to do better in the hike period, we suggest investing in major exporters of commodities.

5.2 Bond Market

Figure 12 shows the time series of the three principle components (level, slope and curvature) of zero rate term structure over the past thirty years. We notice a consistent downward trend in the interest rate level, relatively stable slope and almost constant curvature. When we looked at the growth-driven tightening periods, we observed that the interest rate level usually jumps at the start of a hike. In the longest period from 1994 to 2000 (we combined 1994-1998 hike and 1999-2000 hike together for this analysis as they are only one year apart), there were three major rebounds embedded in the overall downtrend. In contrast, the slope was almost constantly decreasing over the period. We observed a similar behavior of the slope during other tightening periods as well. This confirms our expectation that the short term rate goes up more than the long term rate during a tightening period. We estimated the expected changes in the three principal components using the average historical changes over a year since the

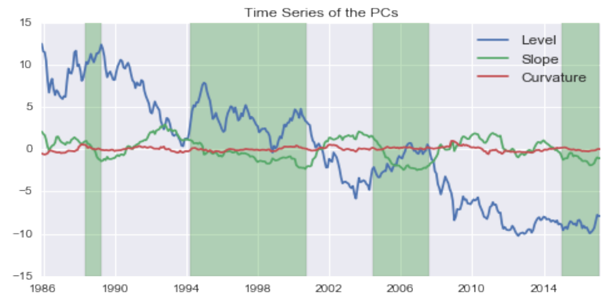

Figure 12: Time Series of Principle of Components

start of a hike. We forecast that the level component will increase by 1.83, the slope component will decrease by 2.25, while the curvature component remains unclear.

Here we give an example of converting our expectation to asset allocation. For simplicity, we assume annually compounded rates and annual coupons:

	P	β_1	β_2	$\mathbb{E}(\Delta P)$	$\mathbb{E}(r)$
1-year zero	98.89	-0.40	0.50	-1.86	-1.88%
3-year 2%	101.88	-1.18	0.66	-3.64	-3.58%
10-year zero	78.14	-2.52	-2.02	-0.07	-0.08%

We use the explained variance of PCs (41.20 bps, 1.64 bps, 0.06 bps) as proxies our estimated factor variance, the covariance matrix of the three bonds is approximately $\begin{bmatrix} 7 & 20 & 40 \\ 20 & 58 & 120 \\ 40 & 120 & 268 \end{bmatrix}$ in bps. The example is informative for allocation of bonds, we expect long term bonds to have better ranking than short term bonds.

6 Conclusion and Discussion

We propose a tactical asset allocation approach based on a historical study of asset performances during previous growth-driven interest rate hike periods. We estimated assets' expected returns from a ranking forecast formed from assets' historical behaviors and our views on the current economic environment. We performed asset allocation using the Black Litterman model, with a variance-covariance matrix estimated through a forward looking RSM-GARCH model.

Based on our asset allocation approach, we determine that a tactical underweight to US Government Bonds and an overweight to US High Yield Bonds would position portfolios well to take advantage of higher growth and narrowing credit risk. Higher expected growth in the US, and by extension globally, justifies the slight overweight to the US stock market and commodities. The US Dollar has not typically done well in growth-driven tightening period. However, as the US is the only major economy entering a tightening period, we expect US growth will continue to support dollar appreciation and thus we overweigh the US dollar. Within the US equity market we conclude that momentum effect will dominate, both in terms of cross-sectional stock picking and sector selection. For bonds, we expect yields to move up faster at the short end than the long end, thus leading to a narrowing of the yield curve slope. We therefore propose a long-short level hedging portfolio to bet solely on the slope of the term structure.

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