ELSEVIER

CrossMark

Available online at www.sciencedirect.com

ScienceDirect

Procedia Economics and Finance 29 (2015) 96 – 121

Procedia Economics and Finance

www.elsevier.com/locate/procedia

The Fifth Joint BIS/World Bank Public Investors Conference

Enhancing the toolbox of fixed income active portfolio management

"R. Violi[a], G. Cellai[a], F. Potente[a], A. Puorro[a]" *

"[(a)] *Banca d'Italia, Financial Investment Directorate, via Nazionale 91, Rome 00184, Italy"*

Abstract

Many central banks adopt an active investment style for reserve management. This paper discusses various possible enhancements to active management tools and processes to generate extra returns in an increasingly challenging environment. The proposed framework is based on an affine model, which includes macroeconomic and market sentiment indicators among the explanatory variables. Using estimates of expected excess returns drawn from the model, an operational indicator produces input highlighting the portfolio's exposure to duration risk. This indicator is incorporated within a broader framework, in which a scorecard considers a range of qualitative elements, including consensus figures on macroeconomic data, monetary policy and interest rates. These elements are then combined with the model output to produce a comprehensive indication with respect to portfolio deviation from the benchmark. It should be noted that the approach presented in this paper is experimental; it has not yet been used in an active portfolio. Finally, consideration is given to the governance of the central bank investment process in order to assess how the proposed enhancements could strengthen the decision-making process. The analysis suggests that the scorecard with model-based input may address some weaknesses inherent in tactical decision- making.

The views expressed herein are solely our own and do not necessarily reflect those of the Bank of Italy or the European System of Central Banks.

Peer-review under responsibility of Organizing and Steering Committee of Fifth Joint BIS/World Bank Public Investors Conference

* Corresponding author: Roberto Violi. Tel.: +39-064-792-4108; fax: +39- 064-792- 94645.
E-mail address: Roberto.Violi@bancaditalia.it

Peer-review under responsibility of Organizing and Steering Committee of Fifth Joint BIS/World Bank Public Investors Conference
doi:10.1016/S2212-5671(15)01116-8

Keywords:
"Fixed income risk premia; business cycle and investor sentiment; active portfolio management; risk-adjusted performance measurement"

1. Introduction

The current financial environment, characterised by very low yields and changes in market microstructure, has highlighted an imperative for active investors to optimise their assessment of market timing, and more generally their capacity to identify potential sources of additional return.

Many central banks adopt a moderately active investment style in managing their foreign reserves as they strive to achieve extra returns on benchmark allocation within parameters consistent with the traditional paradigm of safety, liquidity and return. Against this background, this paper discusses various possible enhancements to central banks' active management tools and processes.

First, we develop a linear affine model in line with a framework set out by Adrian et al (2013), testing a range of specifications in terms of explanatory variables, including macroeconomic, financial stress and sentiment indicators. The estimation is based on monthly data. The model shows statistically significant predictive power for a set of one-month expected excess returns of US bonds along a wide maturity spectrum. The content of information embodied in the estimated time-varying risk premia also includes a tangible value for a portfolio manager, in that the set of predictive variables (risk factors) can significantly expand the opportunity set of feasible risk-adjusted returns from trading US bonds. We go on to demonstrate how such estimates can be used to provide an operational signal – a multifactor quantitative indicator – to position portfolio exposures to certain risk factors, such as duration risk.

In the second step, this multifactor quantitative indicator is applied in conjunction with a scorecard approach. The signal drawn from a strictly empirical analysis of macroeconomic and sentiment indicators is combined with various qualitative indicators: market consensus figures on macroeconomic data, monetary policy, as well as expectations on interest rate developments. The scorecard supports active positioning by reducing subjectivity and supporting synthesis, and delivers a clear operational indication in terms of deviation from the benchmark.

Finally, we attempt to apply these enhancements to a governance framework usually associated with a central bank's active investment process, with the expectation that some adjustments may be necessary to accommodate certain enhancements. Consideration is accordingly given to a number of stylised governance paradigms, taking into account the different hierarchical levels and organisational structures typically involved in the active management process, the tools supporting decision-making and the time horizons. Our analysis shows that many central banks adopt a three-layer decision-making framework that includes an intermediate (tactical) level, which, due to its hybrid nature, may have specific weaknesses. Several features of the scorecard approach – which includes multifactor quantitative input – may effectively address some of these issues.

This paper is organised as follows: in Section 2, recent developments relevant to the context in which official reserve management activity are reviewed. Section 3 outlines the linear affine model and its results. Section 4 describes the scorecard approach. Section 5 moves from the broader theme of central bank investment governance, offering specific suggestions to improve decision-making at the tactical level.

2. A challenging environment for reserve managers

The current financial environment poses serious challenges to central banks acting in their capacity as investors of official reserves.

One particular issue confronting central banks' strategic and active investment decisions in recent years is the exceptionally low level of interest rates. Despite a widespread trend towards greater diversification, central bank investment portfolios typically retain a focus on safe assets whose yields, after 2007, have dropped to unprecedented levels due to a combination of massive supply and demand imbalances[1] and extremely accommodative monetary policies by major central banks.

These low yields reduce the potential returns of central bank asset allocations and may threaten the primary goal of capital preservation; indeed, the current environment introduces scope for significant mark-to-market losses, as rates eventually embark upon a structural, upward cycle. Available evidence[2] suggests that reserve managers now consider a return of rates to normal levels as the most relevant risk for the near future; some are already shifting their investment strategies towards defensive interest rate exposures that mitigate the risk of mark-to-market losses but magnify a negative carry between foreign reserve holdings and sterilisation costs. Central banks may address this issue by replacing safe havens with asset classes that, while improving the overall portfolio risk/return profile based on historical correlation patterns, may reduce liquidity and store-of-value features below normal central bank standards.

The current low-yield environment also represents a real challenge to how traditional central bank active portfolio management[3] has hitherto been conducted. Strategies aimed at generating some extra return on top of the strategic asset allocation by exploiting moderate risk budgets are quite common among official reserve managers. A survey of a group of central banks in the European Union, carried out for the purpose of this study, shows that 20 out of 21 participating central banks adopt a moderately active style in managing their foreign reserves[4] (for further details see Section 3); previous evidence which includes non-European central banks is in line with these findings.[5] Low yields reduce the scope for carry-based strategies, as well as potential income from securities lending. Furthermore, extremely low risk premia and tight spreads potentially limit opportunities for generating excess return by exploiting the credit leeway available to active portfolio managers, as eligible securities other than government bonds provide little yield enhancement and limited protection against adverse spread developments.

Recent regulatory changes and technological innovation over the last few years have affected bond yield dynamics, altering the microstructure of financial markets in which reserve managers operate.

Regulations aimed at limiting banks' proprietary trading activity and introducing strict criteria for permissible market-making are already in place in the United States[6]. Some argue that these changes pose risks to fixed income and equity market liquidity by directly and indirectly constraining dealers' market-making ability. Difficulties in meeting prescriptive criteria for permissible market-making may reduce the level of activity that banks are ready to

---

[1] See Cellai and Potente (2013).

[2] See HSBC Reserve Management Trends (2014).

[3] "Active" portfolio management by central banks is usually characterised by limited exposure to leveraged trades, and cash bond based holding/trading strategies. Provision is made for limited deviations from a benchmark portfolio allocation, with the goal of achieving extra return. A fairly tight tracking-error on their investment strategies helps central banks comply with their self-imposed constraint to limit the market impact of their trading, thereby reducing any associated reputational risk. Therefore, if compared to industry standards, such an approach often blends features of enhanced indexation with those of actual active management.

[4] In September 2014, a survey on a sample of 21 EU central banks was carried out, focusing on active reserve management, with particular regard to the approaches adopted for strategic and tactical allocation and investment governance frameworks. For a summary of the main findings, see Table 4.

[5] See BIS (2009).

[6] In December 2013, the Federal Reserve, the Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation (FDIC), the Securities and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC) approved rules implementing Section 619 of the Dodd Frank Act, commonly referred as Volcker Rule. Banking organisations will have until July 2015 to comply fully, with the exception of banks "with significant trading activities", which will be required to specific reporting obligations starting from July 2014. The Volcker Rule imposes broad restrictions on proprietary trading and investing in hedge funds and private equity funds by banking organisations and their affiliates. Market-making activities are allowed, if conducted in accordance with specific criteria.

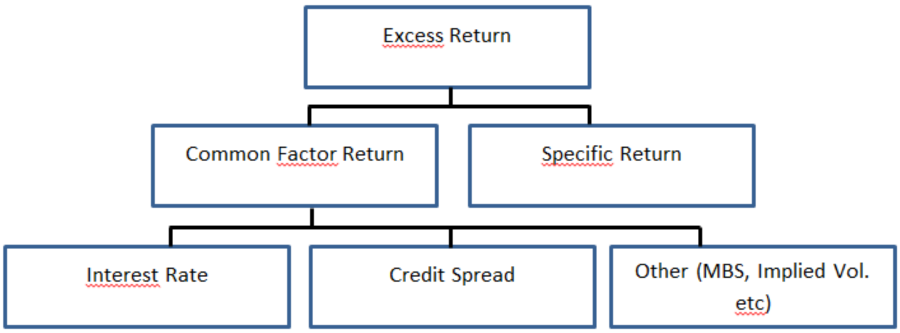
provide.[7] Moreover, the decline in broker-dealer proprietary trading may result in reduced inventories, further restricting overall market-making capacity. In a context where reserve managers seek to expand the universe of eligible asset classes for diversification, such developments may give cause for concern in that they are detrimental to market liquidity and foster volatility, especially in times of market stress. On the other hand, they might also open up arbitrage opportunities for those able to take advantage of them.

Last but not least, recent technological innovation has resulted in widespread use of electronic trading platforms (ETPs), along with an increase in various trading modalities based on computers directly interfacing with ETPs, allowing orders to be placed without immediate human intervention.[8] Professional agents of this kind have a structural competitive advantage based on this state-of-the-art technology, enabling them to trade more rapidly and perhaps even more successfully compared to normal market participants. Such players contribute to higher short-term volatility, thus increasing the complexity of central banks' trading environment. Arguably, these developments, which first materialised in equity markets before rapidly spreading to fixed income, may stimulate central banks to enhance further trading modalities based on economic fundamentals and slightly longer time horizons.

3. Enhancing the quantitative toolbox: factor models of the term structure

Much literature exists – from academics and market practitioners – seeking to identify financial and macroeconomic risk factors contributing to different yield curve configurations over time. This literature is particularly relevant for fixed income portfolio managers as it sheds light on the dynamics of bond returns.

Researchers generally look for factors that persist over time and have compelling explanatory power across a broad range of securities and time buckets. In general, such factors consist of any characteristic with respect to a group of securities that is deemed important in explaining their returns and risks. Factor models decompose individual asset returns into components common to all assets, in addition to a residual component specific to each asset. This approach allows for an intuitive attribution of return and risk to the common systematic components, as well as a robust calculation of correlations between a relatively small number of factors. A typical fixed income model includes common factors such as interest rates and credit spreads, as well as a residual return component that is the result of non-systematic idiosyncratic asset characteristics, such as asset-specific liquidity. The attributed asset return (also referred to as excess return) is calculated by subtracting the predictable return component (due to time variance) from the price return. The following diagram shows the hierarchical decomposition of security excess return.



[7] See O Wyman, "The Volcker Rule restrictions on proprietary trading – Implications for market liquidity", 2012: and US Securities and Exchange Commission, Division of Investment Management, "Guidance Update – Risk Management in changing fixed income market conditions", January 2014.
[8] See Credit Suisse, *Sizing Up US Equity Microstructure*, April 2010; and Hendershott et al (2011).

Interest rate factors can be considered key rates on the term structure. However, since rates are highly correlated, this introduces more factors than are necessary to explain a very high fraction of the variance of all the rates (greater than 95% in most cases; Littermann and Scheinkman (1991)). Using economically meaningful factors that represent a common change for all the rates – specifically shift, twist and butterfly (STB) – reduces the sources of risk without sacrificing accuracy. STB factors represent, respectively, vertical movements of all rates, the steepening and flattening of the yield curve, and changes in curvature. Exposures to STB factors are analogous to duration risk exposure in cases where the interest rate shock is equivalent to a unit change in the level, steepness and curvature (LSC) of the term structure.

In principle, the number of factors used as predictor variables can significantly affect the results of the analysis. For example, Illmanen (1995) uses four factors: term spread, real yield, inverse wealth and momentum. The advantage of this approach is that the bond returns can be directly related to specific financial variables. Cochrane and Piazzesi (2008), on the other hand, use only one factor – expressed as a linear combination of yields or forward capturing all of the economically interesting variation in one-year of expected excess for bonds of all maturities. As a final example, Kim and Wright (2005) fit a three factor constant volatility model to weekly bond data to decompose observed yield and forward curves into expectations of future interest rates and risk premia. Empirical results are different, mixed and time-varying. Furthermore, the quality of the results depends on the point of the curve chosen as dependent variables.

3.1. Linear affine model of the term structure and bond risk premia

Affine models of the term structure of interest rates are popular tools used in analysing bond pricing. The exponential affine framework – see Duffie and Kan (1996) and Dai and Singleton (2000) – is arguably the dominant one in term structure literature. The models typically start with three assumptions: the pricing kernel is exponentially affine in the shocks that drive the economy; prices of risk are affine in the state variables; and innovations to state variables (eg risk factors) and log yield observation errors are conditionally Gaussian.[9] These assumptions give rise to yields that are affine in the state variables and whose coefficients on the state variables are subject to constraints across maturities.[10]

One attractive feature of the framework is that it accommodates negative interest rates, which is very relevant under current market conditions.[11] Another attractive feature is that the martingale component of the factor process does not affect the bond spot yield curve. This implies that one can easily allow for factors that affect prices of interest rate derivatives without affecting bond prices, namely risk factors that are not spanned by the cross-section of yields (eg unspanned risk factors). Assuming that the factor process has diffusive dynamics, the state vector can be partitioned into two kinds of factors that affect the bond yield curve (the term structure of interest rates): factors that affect interest rate volatility but not the term structure (unspanned stochastic volatility, or USV, factors); and those that neither affect the spot yield curve (the term structure) nor interest rate volatility, but may nevertheless indirectly impact the interest rate derivative pricing. Perhaps even more importantly, unspanned risk factors would have an almost imperceptible effect on the cross section of yields (yield curve), while displaying a strong forecast power for bond (holding period) returns and short-term interest rates (Duffee (2009)).

In this framework, the recently introduced class of linear-rational term structure models (Filipovic et al (2014)) can improve the standard exponential-affine class of model, as it accommodates restrictions on interest rate levels and the

---

[9] See Chen and Scott (1993); Dai and Singleton (2000); Collin-Dufresne and Goldstein (2002); Duffee (2002); Kim and Wright (2005).

[10] For overviews, see Duffie and Kan (1996); Piazzesi (2003); Singleton (2006).

[11] The model also can replicate important features of term structure dynamics at the zero lower bound. Consistently with the data, the model may generate extended periods of near-zero short rates as well as highly asymmetric distributions of future short rates, with the most likely value of future short rates being significantly lower than the mean value.

presence of USV factors, while admitting analytical solutions to interest rates derivative, such as caplets, floorlets and swaptions.

Traditional estimation methods for affine term structure models have often treated pricing factors as latent variables that are backed out from observed yields using filtering or observation equation inversion techniques. In following Adrian et al (2013), our estimation approach is different in that it requires the pricing (risk) factors to be observed. Some authors – Joslin, Singleton and Zhu (JSZ, 2011) and Diez de los Rios (2013) – argue that internal consistency needs to be imposed on the model parameters if the principal components (PC) of the yields are used as pricing factors to ensure that the model implied equals the actual principal components. It is worth noting that these consistency restrictions only hold if all model factors represent linear combinations of yields. This is a fairly restrictive assumption, as it would be desirable to include the model risk factors constructed from non-yield data that do not need to be subjected to these restrictions. In contrast with the JSZ model, our approach does not require pricing factors to be linear combinations of yields. Therefore, it can also be readily applied to models that use observable and economically interpretable pricing (risk) factors such as macroeconomic variables and investors' sentiment indicators (or some summary statistics based on an aggregation of them).

Term premia are of economic interest to market participants because they allow inference from the expectation of the path of future short-term interest rates. They are also of special interest to fixed income portfolio managers in that they are a crucial determinant of bond holding period return. However, the relationship between future interest rates and bond risk premia can be subtle, as risk factors that drive risk premia and expected short rates in opposite directions can have arbitrarily small effects on the cross section of yields (yield curve), yet large effects on yield dynamics. Consider, for example, economic news that raises risk premia and simultaneously leads investors to believe the US Federal Reserve will soon cut short-term interest rates. The increase in risk premia induces an immediate increase in long-term bond yields, while the expected drop in short-term rates induces an immediate decrease in these yields. These offsetting effects could be leaving the current term structure – but not the expected future term structures – unaffected by the news.

Recent models of the yield curve have featured unspanned factors[12] that do not affect the dynamics of bonds under the pricing (risk-neutral) measure, but do affect them under the historical measure (see Joslin, Priebsch and Singleton (JPZ, 2012), Duffee (2011) and Wright (2011)). The predictability under the historical measure is consistent with recent academic papers finding that macroeconomic factors have forecasting power for bond returns (see Moench (2008) and Ludvigson and Ng (2009)). The assumption that a given risk factor does not affect the cross section of bond yields under the pricing measure can be implemented by imposing certain restrictions on a set of model parameters.

We illustrate the framework of an affine term structure model with a set of risk factors that can span the risk return space with suitable trading strategies (risk factors that can price the term structure of interest rates). In addition, we also consider predictive variables that may be unspanned by the priced risk factors. This specification can be related to the approach laid out in JPS (2012) and Adrian et al (2013). This model features as pricing factors the first three and five principal components of treasury bond yields. In addition, we extend the range of risk factors to sentiment indicators. We also test whether these additional variables command risk premia, as they drive future bond returns and may impact the spot term structure of interest rates. We want to focus specifically on market sentiment indicators, which, to our knowledge, have not been studied as a risk factor; they may provide additional insights on the yield curve and dynamics of bond returns, and as additional state variables that can have a predictive power for bond returns. It is conceivable that other measures of perceived bond market risk – such as indicators of political uncertainty – might

[12] Unspanned risk factors do not produce contemporaneous effects (or they produce only negligible contemporaneous effects) on expected excess returns. However, they might affect the dynamic of other risk factors (spanned), by also altering the compensation required by the investors for the exposures to spanned factors.

also be worth investigating along the same lines.

Markets react to the release of new information differently, based on its perception about future developments of the macroeconomic situation or risk aversion. Furthermore, other things being equal, the behaviour of bond prices may be affected by the positioning of market players characterised by a more pronounced speculative attitude. Several scenarios may be brought forward in this regard: it is easy to argue, for example, that the release of a poor GDP figure in the United States will have a different impact on the US 10-year yield based on:

- the degree of over/under confidence of market participants about the general economic situation;
- the trading positions of speculative players; and
- the level of investors' risk aversion.

Consequently, a thorough analysis of such market sentiment indicators should be conducted to test the information content of bond excess return. We propose an approach aimed at integrating traditional risk factors with market sentiment indicators.

Our model is based on three market sentiment indicators. The first one is the economic surprise index, which tracks the surprise of economic releases versus market expectations. Stronger-than-expected data positively affects the index, depending, to some extent, on the importance of the data. Such importance is measured by the volatility that the release of the data creates on fixed income markets; eg a series of better than expected data may determine an over-optimistic environment, driving up expectations and increasing the probability of an unexpected bad surprise, in which the impact on securities prices is likely to be high. The second market sentiment indicator is the positioning of speculative operators; when most of the speculative market is positioned on the short or long side, the effect of specific events may prove higher due to market squeezes. The final indicator used in our model is a comprehensive risk aversion index, whose market impact tends to be procyclical in that high risk aversion magnifies the impact of bad news on prices while weakening that of good. Low risk aversion in this regard has the opposite effect.

3.2. Econometric model of the term structure of interest rates

We assume that the dynamics of a vector of risk factors, X_t, evolve according to the following vector auto-regression (VAR) model:

$$X_{t+1} = \mu + \Phi X_t + \upsilon_{t+1}$$

$$\upsilon_{t+1} \sim N(0, \Sigma_x) \tag{1}$$

where μ is a constant parameter vector and Φ is a constant parameter matrix. υ_{t+1} denotes the vector of shocks to the risk factors and $\sum_x$ its variance-covariance matrix. We denote $P^{(n)}_t$ the (zero coupon) treasury bond price with maturity n at time t. The assumption of no-arbitrage implies (see Dybvig and Ross (1987)) that there exists a pricing kernel M_{t+1} such that,

$$P_t^{(n)} = E_t[M_{t+1} P_{t+1}^{(n-1)}] \tag{2}$$

We further assume that the pricing kernel (stochastic discount factor), M_{t+1}, is exponentially affine:

$$M_{t+1} \equiv Exp\left(-r_t - \tfrac{1}{2}\lambda_t' \,.\, \lambda_t - \lambda_t' \,.\, \Sigma_x^{-1/2} \upsilon_{t+1}\right) \tag{3}$$

where $r_t = -lnP_t^{(1)}$ is the continuously compounded risk-free rate. We further assume that the market price of risk function is of the essentially affine form as suggested in Duffee (2002),

$$\lambda_t \equiv \Sigma_x^{-1/2}[\lambda_0 + \lambda_1 X_t] \tag{4}$$

where λ_0 is a vector of constant parameters and λ_1 is a square matrix of constant parameters with dimension dictated by the number of risk factors included in X_t.

We indicate as $rx_{t+1}^{(n)}$ the (log) excess holding period return of a bond with n tenor:

$$rx_{t+1}^{(n)} \equiv lnP_{t+1}^{(n)} - lnP_t^{(n+1)} - r_t \tag{5}$$

Following Adrian et al (2013), we can write the return generating process for log excess holding period returns as

$$rx_{t+1}^{(n)} = \beta_t^{(n)'}\left[\lambda_0 + \lambda_1 X_t - 0.5\, \Sigma_x \beta_t^{(n)} + v_{t+1}\right] - 0.5\sigma^2 + e_{t+1}^{(n)} \tag{6}$$

With

$$\beta_t^{(n)'} \equiv Cov_t\left[rx_{t+1}^{(n)}; v'_{t+1}\right]\Sigma_x^{-1} \tag{7}$$

where the return pricing errors $e_{t+1}^{(n)}$ are assumed to be conditionally independently and identically distributed (i.i.d.) with constant variance, σ^2. We also assume that factor loadings (7) are constant over time[13],

$$\beta_t^{(n)} = \beta^{(n)} \tag{7'}$$

Stacking this system across maturities and time periods, equation (6) can be rewritten as

$$rx = \beta'[\lambda_0 i'_T + \lambda_1 X^-] - 0.5[B\, vec(\Sigma_x) + \sigma^2 i_N]i'_T + \beta' V + E \tag{8}$$

where rx is a $N \times T$ matrix, $\beta \equiv [\beta^{(1)}, \beta^{(2)}, \ldots, \beta^{(N)}]$ is a $K \times N$ matrix of factor loadings, i_T and i_N are a $T \times 1$ and $N \times 1$ vectors of ones, $X^- \equiv [X_0, X_1, \ldots, X_{T-1}]$ is a $K \times T$ matrix of risk factors lagged one period,

$$B \equiv [vec(\beta^{(1)}\beta^{(1)'}),\ vec(\beta^{(2)}\beta^{(2)'}), \ldots, vec(\beta^{(N)}\beta^{(N)'})]'$$

is an $N \times K^2$ matrix, V is a $K \times T$ matrix, which contains the innovations to the risk factors, v_{t+1}, and E is an $N \times T$ matrix with the return pricing errors, $e_{t+1}^{(n)}$.

In order to estimate the set of (price of) risk parameters $[\lambda_0, \lambda_1]$, it is useful to introduce the following OLS style linear projection matrix based on the factor loadings, β

$$H_\beta \equiv (\beta\beta')^{-1}\beta \tag{9}$$

so that we can transform eq (8) into a Seemingly Unrelated Equation (SUR) model with linear regressors, $[i'_T, X^-]$ and coefficients, $[\lambda_0, \lambda_1]$, by multiplying both side of eq (8) by H_β

$$rx_\beta = \lambda_0 i'_T + \lambda_1 X^- + E_\beta \tag{10}$$

---

[13] It is left for future research to relax the assumption of constant factor loadings.

with

$$rx_\beta \equiv H_\beta rx + 0.5\, H_\beta[Bvec(\Sigma_x) + \sigma^2 i_N]i'_T - V;\;\; E_\beta \equiv H_\beta\, E \quad (10')$$

3.3. Maximal Sharpe ratios and the investment opportunity set of portfolio strategies

The linear affine model of the term structure gives us a reasonably simple way to construct maximum (conditional) Sharpe ratio (MSHR). In particular, Gaussian models give a clean interpretation of the model-implied conditional Sharpe ratios. Because the models rule out time variation in conditional covariances, model-implied Sharpe ratios are best thought of as expected excess returns divided by average standard deviations. MSHR is a typical tool for assessing risk-adjusted performance in a classic asset allocation exercise and is also a valuable indicator, in a dynamic setting, for examining the variation in investment opportunities. It could also provide a good sanity check in a model evaluation exercise; for example, very high model implied MSHR levels are likely to raise questions about the practical relevance of such a model.

The Sharpe ratio is maximised for a hypothetical return to a portfolio of bonds that replicates the payoff to the log pricing kernel (stochastic discount factor) exactly. The model-implied maximal Sharpe ratio (SHR) therefore corresponds to[14]

$$\underset{w_t}{\mathrm{Max}}(SHR) = \sqrt{Var_t[Log(M_{t+1})]} = \sqrt{\lambda_t'\ \lambda_t} \quad (11)$$

where w_t is the optimal portfolio maximising the Sharpe ratio and λ_t is the price of risk factors. The expected excess return to an n-period bond from t to $t + 1$ can be derived from eq (6) and it is given by

$$\text{Expected Excess Return}^{(n)}(\text{EER}) \equiv \beta^{(n)\prime}\left[\lambda_0 + \lambda_1 X_t - 0.5\Sigma_x \beta^{(n)}\right] - 0.5\sigma^2 \quad (12)$$

It should be noted that expected excess returns the time-varying component of the excess return to

$$\text{Time-Varying }\_EER^{(n)} \equiv \beta^{(n)\prime}\lambda_1 X_t \quad (13)$$

which shows that changes in the risk factors – weighted by the price of risk parameters, λ_1, and the factor loadings, $\beta^{(n-1)}$ – are the drivers of the time-varying expected bond return.

The maximal Sharpe ratio provides a useful diagnostic of the validity of the stochastic discount factor specification assumed in the model. Duffee (2010) argues that certain (linear affine) factor models of the term structure can give rise to excessively high maximal Sharpe ratios due to over-fitting. A reasonable set of parameter estimates should avoid unrealistic Sharpe ratio levels. In this case, MSHR could provide a useful indicator about the investment opportunity set available to portfolio managers. As a risk-adjusted performance measure, MSHR also decomposes the contribution of each risk factor to the overall performance. This is a useful tool for active trading strategies aimed at timing the changes in the level of risk premia.

3.4. Estimation procedure

[14] See also Adrian et al (2013).

In our baseline specifications, we use linear combinations of log yields (such as principal components) as observable factors X_t and estimate the model parameters using holding period returns based on the same set of yields. We follow Adrian et al (2013) and we proceed with the assumption that the factor loading matrix, β, is constant.

We estimate eq (1) via ordinary least squares achieving a decomposition of X_{t+1} into a predictable component and an estimate of the factor innovation v^*_{t+1}. We recombine these innovations into the matrix, V^* for an estimate of the state variable variance-covariance matrix[15],

$$\Sigma^*_x = V^* V^{*\prime}/T \tag{14}$$

In the second step we regress excess returns on a set of pricing factors lagged one period and a set of contemporaneous risk factor innovations – with a constant added – according to the following transformation of eq (8)

$$rx = ai'_T + \beta' V^* + cX^- + E \tag{15}$$

With

$$a \equiv [\beta'\lambda_0 - 0.5(B\, vec\,(\Sigma_x) + \sigma^2 i_N)i'_T;\, c \equiv \beta'\lambda_1$$

Collecting the regressors into the $(2K+1)\; x\; T$ matrix $Z^* \equiv [i_T, V^{*\prime}, X^-]'$, the OLS estimators become

$$[a^*, \beta^{*\prime}, c^*] = rxZ^{*\prime}\left(Z^* Z^{*\prime}\right)^{-1} \tag{16}$$

Next we collect the residuals from this regression into the $N \times T$ matrix E^*. We then estimate

$$\sigma^{*2} = tr\left(E^* E^{*\prime}\right)/NT$$

with: $E^* \equiv rx - [a^*, \beta^{*\prime}, c^*]\, Z^*$

We construct B* from the estimates, β*, and we proceed to estimating the price of risk parameters $[\lambda_0\ \lambda_1]$ via the cross-sectional regression (10), using the following eq (10') estimate,

$$rx^*_\beta = H^*_\beta rx + 0.5\, H^*_\beta [B^* vec(\Sigma^*_x) + \sigma^{*2}\, i_N] i'_T - V^* \tag{17}$$

we can then implement the multivariate (SUR type) regression model (10) with $[\, i'_T, X^-]$ as identical regressors in each of the K equations,

$$rx^*_\beta = \lambda_0\, i'_T + \lambda_1 X^- + E_\beta \tag{18}$$

In the third and final step we estimate the λ_0 and λ_1 estimate parameters in compact form:

$$\Lambda = (W'\Omega^{-1}W)^{-1}\, W'\Omega^{-1}\, RX_\beta \tag{19}$$

Where:

---

[15] For a detailed presentation of a regression-based approach using a linear pricing kernel specification, see Adrian et al (2013).

$$\Lambda = [\lambda_{0,1}, \lambda_{1,1}, \dots, \lambda_{0,K}, \lambda_{1,K}] \qquad (K+1)K \times 1$$

$$\mathrm{R}X_\beta = [rx^{*\prime}_{\beta,1}, \dots, rx^{*\prime}_{\beta,k}] \qquad TK \times 1$$

$$X^* = [i_T, X^{-\prime}] \; T \times (k+1) \quad \text{and} \quad W = \mathrm{Kron}[I_K; X^*] \;\; TK \times (K+1)K$$

$$\Omega = \mathrm{Kron}[(H^*_\beta \, \Sigma_E \, H^{*\prime}_\beta); \, I_T] \; TK \times TK \quad \text{and} \quad \Sigma_E = EE'/T \quad N \times N$$

This is GLS representation where the covariance error matrix depends on the second step. Due to identical regressors, this representation is the same as the OLS equation by equation strategy.[16]

3.5. Empirical results

In this section, we provide estimation results for a number of econometric specifications. We use the principal components of treasury yields as our basic set of risk factors in modeling US Treasury bond returns. Early research by Scheinkman and Litterman (1991) points out that three factors are enough to explain the cross-sectional variation of yields. More recent papers, such as Cochrane and Piazzesi (2005, 2008) and Duffee (2011), and emphasise the importance of additional factors to explain treasury returns. We therefore choose K=3 and K=5 factor specifications as our baseline examples. We also estimate models with additional risk factors, adding to the yield-based set of risk factors two macroeconomic variables and a proxy for investors' sentiment indicator. All in all, we investigate five estimated versions of the model according to the following structure of risk factors:

- 3 principal component implied by bond yield curve changes (YCC factors: Level, Slope, and Curvature; LSC)
- 5 principal component implied by bond yield curve changes (3 LSC factors + 2; 5 YCC factors)
- 5 YCC factors + 1 sentiment indicator
- 3 YCC Factors + 2 macroeconomic variable
- 3 YCC factors + 2 macroeconomic variable + 1 sentiment indicator

Taking as given the set of risk factors included in each of the five model specifications, we estimate the main parameter $(\phi, \Sigma_x, \sigma, \beta, \lambda_0, \lambda_1)$ using the approach described above. We discuss estimation results for various specifications in the next section.

Concerning term structure data, all estimated models use bond returns computed from constant maturity (coupon paying) government securities from the set of constant maturity treasury yields published in the Federal Reserve Board (H.15 release). We use a cross section of yields for maturities n = 12, 24, 36, 60, 84, 120, 240 months. From these yields we extract their principal components. We calculate holding period returns for a hypothetical set of par coupon bonds based on the chosen yield dataset with a full revaluation method.

Taking as the risk-free rate the n = 1 month bill yield, r_t, and subtracting it to each holding period return, it gives us the cross section of excess returns for N = 7 maturities,

$$rx^{(n)}_{t+1} \equiv r^{(n)}_{t+1} - r_t \tag{20}$$

Also, we use the time changes of yield to maturity to compute 3 and 5 first principle components that are used as risk factors in our set of estimated models. Table 1 reports some descriptive statistics of the observed holding periods' excess returns based on the set of constant maturity yields adopted for our estimates.

[16] See, for instance, Greene, 7th edition, paragraph 10.2.2.

Table 1: Descriptive statistics

	1 year	2 year	3 year	5 year	7 year	10 year	20 year
Mean	0.05%	0.09%	0.14%	0.21%	0.28%	0.35%	0.51%
Std	0.19%	0.42%	0.67%	1.12%	1.53%	1.93%	2.88%
Skewness	1.4422	0.395	0.0217	–0.052	0.1242	0.63432	1.03937
Min	–0.38%	–0.97%	–1.59%	–2.69%	–3.95%	–5.14%	–7.04%
Max	0.79%	1.33%	1.92%	3.95%	6.38%	10.18%	16.45%

All models are estimated over the sample period August 2001–August 2014, which provides a total of $T = 157$ monthly observations. Following the empirical evidence for yield risk factors based on 3 and 5 principal components, we estimate the set of predictive equations and test for the significance of the associated risk factor pricing coefficients, $[\lambda_0 \ \ \lambda_1]$. We compute observed, fitted and expected excess returns time series for each maturity. Fitted returns are given by

$$\beta^{*\prime}(\lambda_0^* \, i'_T + \lambda_1^* X^- + V^*) - 0.5[Bvec(\Sigma_x) + \sigma^2 i_N]i'_T \tag{21}$$

which includes risk factor levels, X^-, as well as their innovations, V*. However, the expected excess returns measure,

$$\beta^{*\prime}(\lambda_0^* \, i'_T + \lambda_1^* X^-) - 0.5[Bvec(\Sigma_x) + \sigma^2 i_N]i'_T \tag{22}$$

excludes the innovations to the risk factor, V*, as their expected value is zero. In both fitted and expected returns factor loadings matrix, $\beta^{*\prime}$, weights the price of risk component,

$$(\lambda_0^* \, i'_T + \lambda_1^* X^-) \tag{23}$$

While the convexity adjustment term

$$-0.5[Bvec(\Sigma_x) + \sigma^2 i_N]i'_T \tag{24}$$

can be ignored for all practical purposes as it is likely to be small.

Charts (1) and (2) report observed, fitted and expected returns for the 7-year constant maturity bond based on the 3 and 5 risk factors model. In both cases, they display a very high level of (in sample) fitting with an R^2 statistics of around 98-99%.

Chart 1

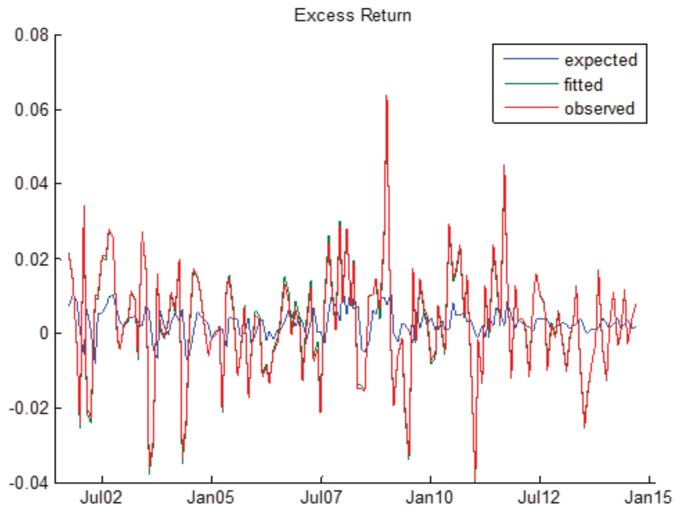


Chart 2

Not surprisingly, expected returns are much less close to actual returns than fitted returns, as the latter incorporates risk factor innovations, which are very important drivers of holding period bond returns. Moreover, expected returns are far less volatile than realised returns. Both econometric specifications fit the cross section of returns nearly perfectly and give rise to substantial time variation in the prices of risk. All in all, the term premia implied by the expected returns show a significant predictability component embodied in the risk factors' time variation: taken together their variability over time can account for 5-7% of excess returns variability as measured by the reported R2 statistics. The 3 and 5 bond yield-based risk factors turn out to be priced risk factors, as their risk parameters $[\lambda_0 \quad \lambda_1]$ are statistically significant; however, this happens with a clear-cut outcome only for the 3 factor (LSC) version of the model, while the evidence regarding the additional 2 yield based factor over and above LSC is less strong.[17]. Charts (3) and (4) plot the Maximal Sharpe ratio (MSHR) associated with the 3 and 5 bond yield risk factors model specifications. As they are priced, time-varying risk factor premia are positive and fluctuating over time.

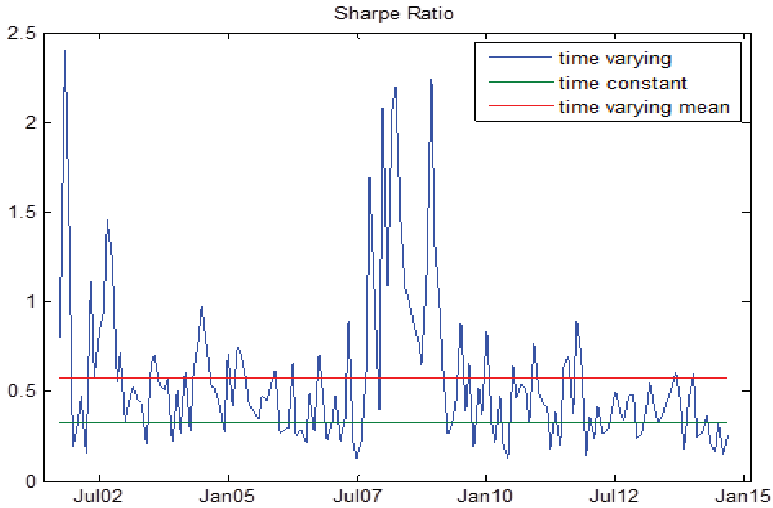


Chart 3 (3 YCC factor model)

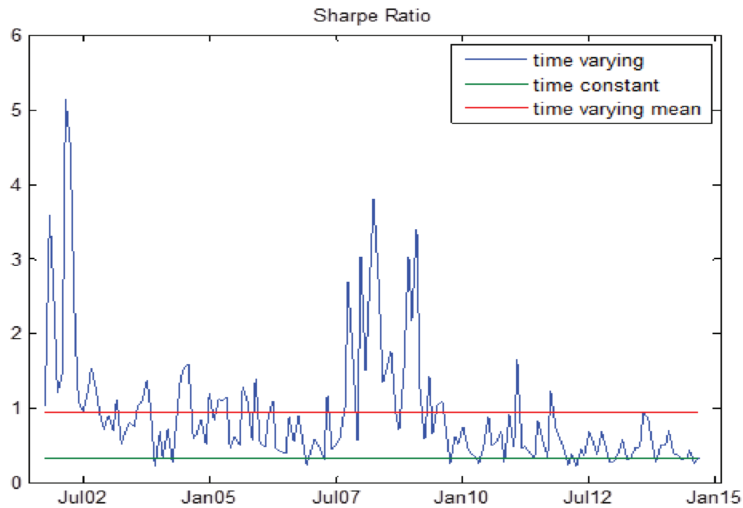


Chart 4 (5 YCC factor model)

[17] A full set of statistical tests for all models is available from the authors upon request.

The estimated MSHR tends to oscillate around 0.55 for the 3 factor YCC model and around 1 for the 5 YCC factor model (their respective sample average), with a few temporary spikes above 2 and 3 around the time of recession and/or financial crisis, such as around September 2001 and during the 2007-08 bursting phase of the 2007 financial crisis. These occurred at times when the Fed was in the process of drastically changing its policy stance in the face of very significant negative macroeconomic shocks. While showing some similarity in their dynamic pattern, the average MSHR across these models shows a tangible difference, as the 5 factor model almost doubled the level of risk-adjusted expected returns compared to the 3 factor model. This large difference in expected risk-adjusted return across models might be driven, at least in part, by treating the additional fourth and fifth factors as spanned factors. However, at least in principle, even if additional factors 4 and 5 have a minor impact on the yield curve, they can add a fairly large value to the pursuit of active trading strategies trying to chase time-varying risk premia of the term structure by choosing a suitable portfolio of bonds with different maturities and adjusting its composition over time.

The horizontal line reported in the charts in green represents the special case of time-invariant expected returns with constant risk (term) premia, which is obtained by setting,

$$\lambda_1^* = 0 \tag{24}$$

Eq (24) is equivalent to the restriction implied by the generalised expectations hypothesis of the term structure (GEHTS; Sangvinatsos and Wachter (2005)), whereby term premia are assumed to be constant. The estimated MSHR in this case equals 0.2 for the 3 yield-based factor model and 0.4 for the 5-yield-based factor model. While the restriction (24) is strongly rejected by the data, it provides a useful benchmark for gauging the investment opportunity set (eg trading strategies) available to investors as they rely on the predictability of priced risk-factors in their attempt to time bond term premia. Interestingly, the MSHR indicator for both models shows a declining trend after the 2009 recovery in the United States, moving closer to its floor given by a constant level of the term premium. Hence, at this juncture the GEHTS may provide a realistic description of the risk priced by the current term structure of interest rates.

We now move on to models where we include macroeconomic indicators for consumer price inflation and economic growth as well as a proxy for investor sentiment in our set of risk factors. Recent models of the yield curve have featured unspanned factors that do not affect the dynamics of bonds under the pricing measure, but do affect them under the historical measure (see JPS (2012); Duffee (2011); Wright (2011) and Adrian et al (2013)). According to the empirical evidence reported in this literature, it is not always clear if these variables can be treated as a priced risk factor. The assumption that a given risk factor does not affect bond yields under the pricing measure can be implemented by imposing the restriction that the corresponding elements of $[\beta^{(n)}, n = 1,2, \dots , N]$ be exactly equal to zero. Under the assumptions we made in Section 3.2, one can show that bond prices are exponentially affine in the vector of state variables:

$$lnP_t^{(n+1)} = A_{n+1} + \beta^{(n+1)\prime} X_t + u_t^{(n+1)}$$

From the equation (5), it follows

$$A_{n+1} = A_n + \beta^{(n)\prime}(\mu - \lambda_0) + 0.5\left(\beta^{(n)\prime}\Sigma_x\beta^{(n)} + \sigma^2\right) + A_1$$

$$\beta^{(n+1)\prime} = \beta^{(n)\prime}(\phi - \lambda_1) + \beta^{(1)\prime} \tag{25}$$

valid starting from n=1, whereas $A_0 = 0, B_0 = 0, A_1 = -\delta_0, B_1 = -\delta_1$

with the following expression for the log bond pricing errors,

$$u_{t+1}^{(n)} - u_t^{(n+1)} + u_t^{(1)} = e_{t+1}^{(n)} \tag{25'}$$

recalling that $r_t = -lnP_t^{(1)} = -A_1 - \beta^{(1)\prime}X_t - u_t^{(1)}$

$r_t = \delta_0 + \delta_1{}'X_t + u_t^{(1)}$, which represents the equation describing the dynamic of the short-term rate as a function of risk factors.

According to statistical tests reported in the literature, risk factors are thought to be unspanned if their loadings on the yield curve do not reject the null hypothesis that

$$\beta \equiv \left[\beta^{(SP)}; \beta^{(US)}\right],\ \beta^{(US)} = 0 \qquad (26)$$

where the superscript US indicates the set of parameters associated with the risk factors subject to the unspanning test (unspanned risk factors), while the superscript SP corresponds to the set of factor loading for the spanned risk factors. If restriction (26) is not rejected, the corresponding factors are irrelevant for bond pricing – ie they do not contribute to the shape of the term structure of interest rates.

Restriction (26) is also important for the price of risk parameter estimates, $[\lambda_0\ \ \lambda_1]$, as witnessed by the second step of our estimation procedure (see eq 17-19'). Such estimates determine the MSHR indicator measurement. More specifically, the issue here is how the restriction (26) has an impact on identifying the price of risk parameters corresponding to the unspanned risk factor. We can conveniently complement the pricing implications of restriction (26) by testing the null hypothesis that certain rows/columns of $[\lambda_0\ \ \lambda_1]$ are equal to zero for unspanned risk factors. Operationally, we can proceed by introducing a suitable decomposition for the price of risk matrix, $[\lambda_0\ \ \lambda_1]$ by distinguishing the spanned versus the unspanned price of risk factors as follows:

$$[\lambda_0\ \ \lambda_1] = \begin{bmatrix} \lambda_0^S & \lambda_1^{SS} & \lambda_1^{SU} \\ \lambda_0^U & \lambda_1^{US} & \lambda_1^{UU} \end{bmatrix} \qquad (27)$$

One possible way to tackle the identification problem with matrix (27) would be to effectively set to zero the lower rows of the price of risk parameters – corresponding to the unspanned risk factors – without imposing any a priori restrictions to the upper right block of λ_1

$$\lambda_0^U = 0, \lambda_1^{US} = 0\ , \lambda_1^{UU} = 0, \lambda_1^{SU} \neq 0 \qquad (28)$$

where λ_1^{SU} corresponds to the price of risk in the set of spanned risk factors induced by the exposure to the set of unspanned factors. However, the recursion scheme for the factor loadings β in eq (25) and the restriction (26) for the unspanned factor also requires that:

$$\lambda_1^{SU} = \Phi^{SU} \qquad (28')$$

We test restrictions (26) for all our specifications, with the exception of the 5 yield-based risk factor model. We summarise our results in Table 2 for all models. Our main conclusions regarding the risk factors classification are as follows:

The LSC risk factor model is considered only as having spanned and (fully) priced risk factors by the bond yield curve (we do not run any tests about the hypothesis of unspanned risk factors in the specification with 5 PC risk factors).

- The YCC 5 (3 LSC + 2) risk factor model possibly has 2 unspanned risk factors (corresponding to the fourth and fifth principal component implied by the bond yield curve).
- The set of macroeconomic risk factors does not reject the null hypothesis of being classified as unspanned risk factors.
- The investor sentiment risk factor does not reject the null hypothesis of being classified as an unspanned risk factor.

Table 2: Risk factors

	Rq fit	Rq exp	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	SENTIMENT	PCE	CFNAI
3 PC	0.9842	0.0564	S	S	S					
3 PC+2 MACRO	0.9845	0.0748	S	S	S				U	U
5 PC *	0.9940	0.0715	S	S	S	S	S			
5 PC + SENT	0.9940	0.1423	S	S	S	U	U	U		
3 PC + 2 MACR + SENTIMENT	0.9847	0.1576	S	S	S			U	U	U

(*) In this model specification the 2 additional YCC factors – over and above the 3 LSC factors - are assumed to be spanned

It is worth noting that unspanned risk factors can provide useful information for asset pricing models whose main goal is to account for the time-varying components driving expected returns. More specifically, the fact that unspanned risk factors do not impact the bond yield curve do not make them redundant as far as bond returns are concerned. As discussed above, this is a fairly subtle point in the identification process that is not well understood in the literature, but has important practical implications for active portfolio managers.

In our sample data, the set of unspanned risk factors includes the set of macroeconomic variables and the investor sentiment indicator (Table 1). As far as the R^2 measure is concerned, investor sentiment has significant impact as it doubles its level to over 14%; the set of macroeconomic variables shows a very model additional effect (R^2 just over 15%). They seem to provide a tangible improvement in the MSHR indicators (risk-adjusted potential performance), as its average increases from 0.55 to 0.75 when measured again the 3 risk factor LSC model.

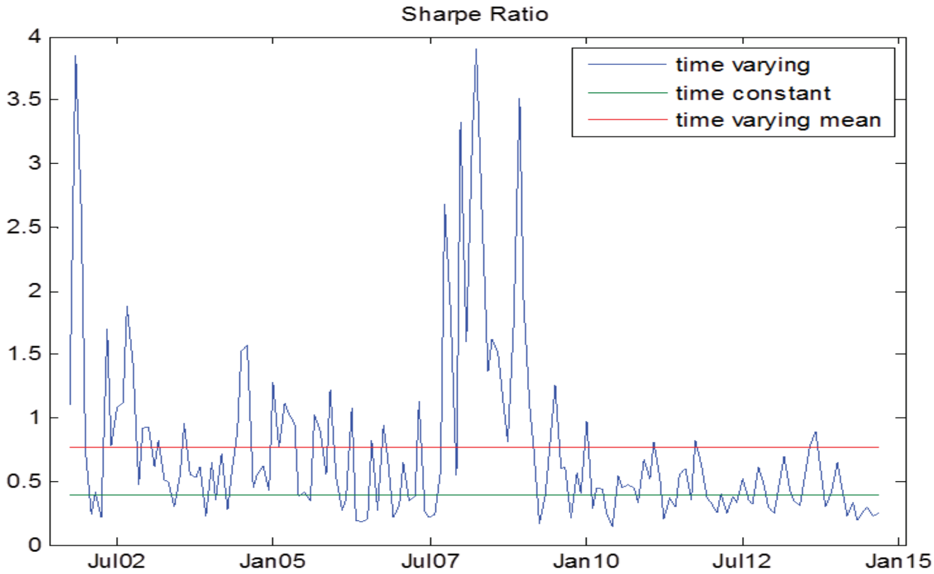


Chart 5 (3 YCC risk factors + 2 macro variables + 1 investor sentiment indicator)

Finally, in order to draw operational signals (long/short duration) from the model estimates, a multifactor quantitative indicator (MQI) is elaborated below, with a view to feed it into a scorecard approach.

As our model provides an estimate of expected excess returns, a positive excess return could signal a long duration period, assuming that the financing cost of the long position in the portfolio equals the 1-month bill return (by contrast, a negative excess return points to a short duration position). A simple and intuitive way to construct the MQI could be as follows: a tenor that is relevant for the portfolio (eg seven years) is selected and the expected excess return provided by the model is divided by its rolling standard deviation, so as to standardise the figure. The value can be left unconstrained or capped in a desired range [–2, +2]. The first option would assign a greater significance to the indicator, compared to other factors used in the scorecard proposed below.

$$\mathrm{MQI} = \frac{EER}{std(EER)} \tag{29}$$

4. Integrating quantitative and qualitative information into a central bank's active management process: a scorecard approach

Whereas quantitative indicators may seem invaluable for taking into account market uncertainty, they nevertheless have drawbacks; fully automated decision-making processes tend to be profitable over very short time horizons, often as a consequence of market inefficiencies. As time horizons lengthen, however, sudden and significant changes in the set of available information become more likely, thereby undermining the ability of quantitative indicators to support the search for stable extra performance. On the other hand, qualitative assessments involve a degree of subjectivity, reflecting each individual's evaluation of available information, which may be biased by personal opinions or behavioural factors. This judgmental element may, of course, be reduced by means of a structured process selecting the inputs of qualitative assessments (eg recourse to consensus data, professional forecasts).

In this context, a scorecard approach can be useful in minimising many discretion-related weaknesses intrinsic to purely qualitative approaches, and in allowing scope for an effective combination of quantitative and qualitative input, blending different signals into an operational indicator. Furthermore, scorecards could represent a means for reconciling diverging signals and supporting collegial decision-making by fostering a consensus to converge on scorecard input variables as well as on weightings.

In Table 3 below, we provide an example of a three-section scorecard that combines the information derived from the affine model (as described above) with qualitative elements, producing a comprehensive indicator suitable for supporting central bank active investment decisions, ideally with a one- to three-month time horizon.

Table 3: Scorecard example

Section	Indicator	Scoring (eg + 2, –2)	Weight %	Comments
1	**Quantitative indicator (2)**	+0.5	**33%**	The quantitative indicator points to the long side, but the signal is weak.
2	**Macro-economic consensus** • US GDP expectations • US CPI expectations • FOMC Monetary policy decision expectations	 + 1 + 0.5 + 1	**34%** 11.4% 11.3% 11.3%	There are expectations of a slowdown in growth, subdued inflation and an accommodative monetary policy stance.
3	**Financial variables** • Market consensus on rates on specific tenors • Market consensus on US Treasury curve slope	 0 -1	**33%** 16,5% 16,5%	The market consensus is in line with forward rates; extremely compressed term premium

Section 1 represents the quantitative indicator drawn from the estimates provided by the affine model. In this case, the normalised value is 0.5, signalling a moderate downside pressure on US yields; the weight of the quantitative indicator is set at 33%.

Section 2 focuses on GDP and CPI consensus figures, as well as expectations on the Fed's monetary policy; each element is weighted at just above 11%.

Section 3 includes consensus financial variables, based on Reuters polls about the future level of the 10-year US Treasury yield over the relevant time horizon and on market consensus figures on the US yield curve slope (two- to 10-year differential). Both are weighted at 16.5%.

It is interesting to note that, in a context characterised by unconventional monetary policies like those prevailing over the last few years, the importance of monetary policy measures grows, as exceptional liquidity conditions may override other factors. Therefore, weights should be calibrated accordingly. In addition, in an extremely low rate environment, where monetary policy is often implemented through outright purchases of securities, the impact of such measures along the yield curve should also be considered while calibrating monetary policy weights for different curve buckets.

For each factor, a positive score supports a rate decrease (long position), while a negative score supports a rate increase (short position). The score value reflects the magnitude of the expected impact of a specific factor: values of +2 (–2) mean that the current expectations are particular strong (weak), while a zero means that expectations are in line with past average values.

Therefore, raw data must be standardised: for example, a GDP consensus figure at 2.5% requires the calculation of a Z score[18] and then the standardisation of the Z score into a range (+2, –2 in the example). The value is calculated on a rolling window.

$$\boldsymbol{Z}GDPexp = -\left(\frac{GDPexp - \boldsymbol{\mu}GDP}{\boldsymbol{\sigma}GDP}\right) \tag{30}$$

At first sight, inclusion of the multifactor analytical indicator as a key input of the scorecard, together with macroeconomic and financial variables, may seem like an instance of input duplication. In other words, the same kind of data being used to construct the quantitative indicator may appear to feed into Sections 2 and 3 of the scorecard. However, this is not true. Sections 2 and 3 are not concerned with actual data or sentiment indicators, but rather include market consensus figures on economic and financial developments. Bloomberg and Reuters provide updated figures on a continuous basis, adequately addressing the need for data reflecting changes in expectations related to new, incoming information.

It is also important to recognise that the set of macroeconomic and financial variables is pre-defined but flexible. First, each scorecard user assesses the relative importance of each variable at that specific point in time;[19] this assessment determines the actual selection of the set of variables to be used in the scorecard, within the broader universe of potentially eligible factors, as well as the calibration of relative weights of variables and sections. As a base case, all three sections are equally weighted in the example above.

As a second step, a weighted average of the scores is calculated, indicating the side and magnitude of the position. In

[18] The Z-score is multiplied by -1 because the scorecard output is a position vs benchmark, that will be positive/long in case negative Z-scores related to macroeconomic and financial variables (eg very negative GDP consensus will produce a positive output in terms of duration exposure vs benchmark).

[19] For example, among growth-related variables, GDP data may prove more relevant than employment data, depending on the general macroeconomic context; among monetary policy-related variables, central bank balance sheet developments may – at times – be a more significant driver for the market than policy rates.

the example, the weighted average (WA) is 0.2835, pointing to a moderately long position that compares with a maximum possible weighted average of 2.

Finally, a risk budget to be managed through the scorecard is defined, so that a +/–2 WA would encompass the usage of the entire budget on the long/short side, while WA between –2/+2 would bring about a proportional usage of the budget. Assuming a 40 basis point risk budget in terms of duration, the WA as of the example would result in +5.67 duration basis points versus the benchmark.

$$\frac{\boldsymbol{WA}}{\text{maximum score (abs.)}^{20}} \times \text{risk budget}$$

$$\frac{\mathbf{0{,}2835}}{\mathbf{2}} \times 40 = 5{,}67 \text{ bp}$$

It should be clearly noted that, in order to be implemented within the portfolio, the above indication requires a further step; namely an assessment of how to establish the long positioning on the relevant segments of the yield curve. Any such assessment can be made by the portfolio manager independently of the scorecard; alternatively, it may be deemed appropriate to produce two or more ad hoc scorecards for the curve segments in question (eg two and seven years), each incorporating the corresponding quantitative indicator and the macro and financial variables considered most significant for the selected maturities. In this case, the risk budget would be allocated along the curve consistently with the output of the scorecards.

5. Fitting the tools into the governance framework

Active fund management by central banks is usually framed within a robust and well designed governance structure, allocating responsibilities across appropriate hierarchical levels, providing clear rules for the delegation of authority, while also ensuring an adequate distinction between reserve management responsibilities and those related to institutional functions.[21]

The governing board typically makes strategic decisions about the desired trade-off between risks and returns and the related asset allocation, establishing the key features of the investment framework. Optimisation processes aimed at determining the best strategic asset allocation (SAA), given policy objectives, return preferences and investment constraints, are widely used to guide the decision-making bodies. SAA time horizons vary considerably among central banks. In principle, decisions of this kind may be regarded as relatively structural; some central banks have no pre-defined time horizon for SAA, instead carrying out only ad hoc reviews. In fact, shorter time horizons ranging between one and three years seem to be the most common approach.[22]

The active portfolio management layer of the governance framework implements the actual reserve management strategy and takes additional risk within pre-defined budgets, with the aim of generating extra return. The relationship between the governing board and the portfolio management layer can be stylised as a principal, whereby the board, as the principal, delegates some risk-taking to staff, acting as an agent within predetermined limits; a further distinction can be made between agents charged with taking financial risks and those responsible for monitoring and control.[23] Committees are often introduced at different levels of the governance framework, offering the benefit of group decision-making and information processing. The governing board may delegate specific tasks or receive advice from

[20] In the example as of Table 3, the maximum possible score (in absolute terms) is 2.
[21] See: IMF (2013) ,Section C.
[22] See footnote 3.
[23] See BIS (2013).

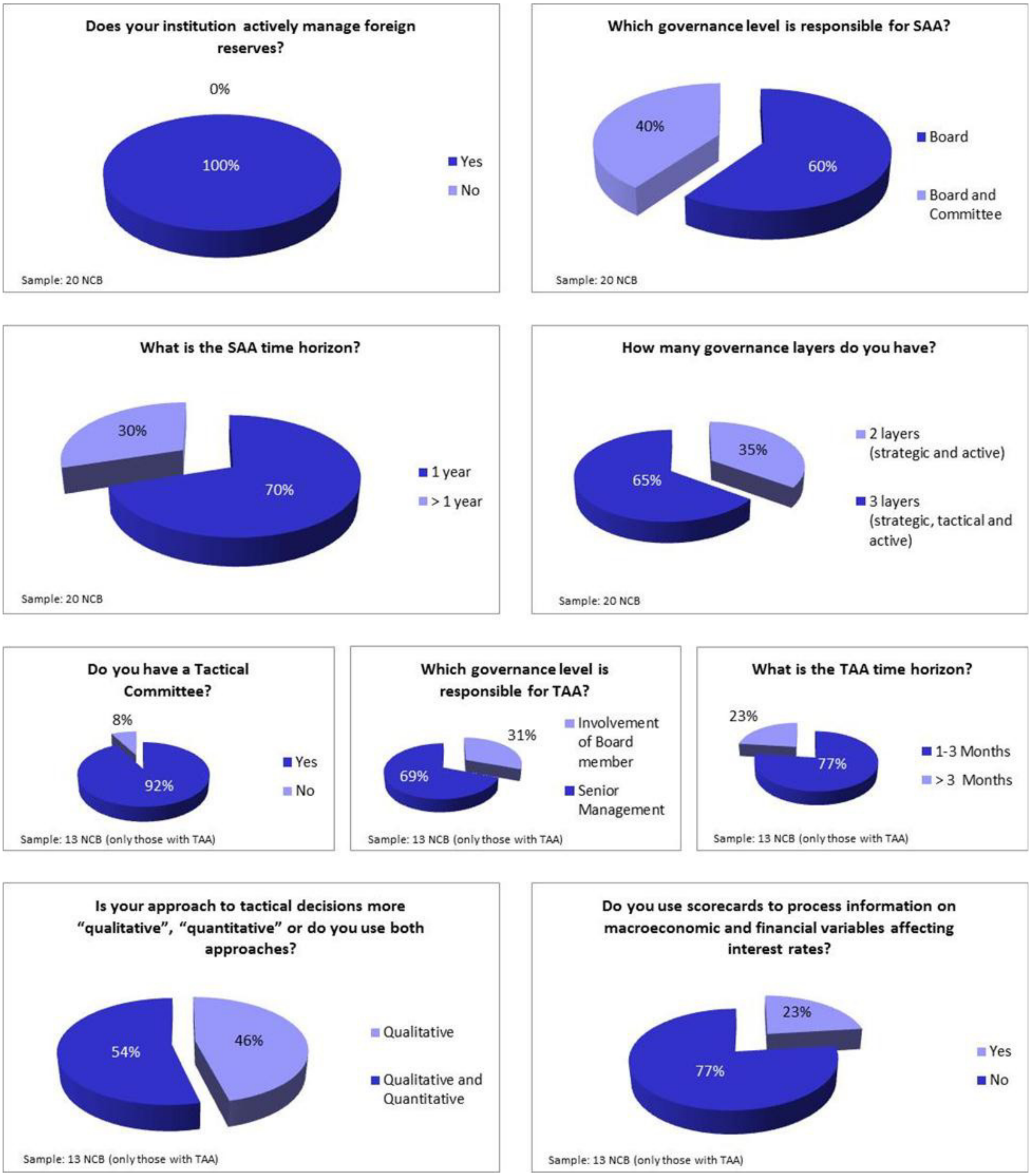
a high level/strategic committee, while some decisions concerning the implementation of strategies may be delegated to an investment committee.

In point of fact some central banks that actively manage their reserves adopt a governance that includes an intermediate, tactical level, whereby the investment committee is directly involved in actual risk-taking, with the overall active risk budget being allocated between the investment committee and the portfolio management level. The measurement and reporting of the results of each active level ensure accountability and a clear distinction of responsibilities.

The survey conducted for the purpose of this study[24] reveals that, out of 21 central banks actively managing their reserves, 13 adopt a three-layer framework, usually including a tactical/investment committee (Table 4). These committees differ in terms of composition, participating hierarchical levels and time horizons. In most cases, the committee involves senior management of the operations department, but it is not uncommon to have top management participate in tactical asset allocation (TAA) by way of an executive board approving decisions or a board member chairmanship overseeing the investment committee. In terms of time horizons, the survey shows a majority of central banks focusing on the one- to six-month range for TAA, though some extend it to one year. The survey also shows the degree to which approaches for elaborating tactical asset allocation may vary. All central banks assign a key role to a qualitative assessment of expected interest rate developments, based on factors such as economic fundamentals, technicals and market positioning; a minority of central banks use scorecards or other scoring systems to process such information. In some cases, the resulting interest rate scenario is translated into tactical positioning without any quantitative support; more frequently, the qualitative assessment feeds into quantitative analysis, with the aim of establishing a tactical benchmark portfolio through an optimisation process, or simply calibrating and validating the size of positions.

[24] See footnote 4.

Table 4: Survey on reserve management governance and tools (21 EU central banks, September 2014)



Some central banks choose an investment framework that includes the intermediate active level, which often creates an additional benchmark with an objective function of outperforming strategic asset allocation. Furthermore, it is quite specific to central banks; this level is not otherwise found within the asset management industry.

Within this industry, in general, the principal/agent model is the cornerstone of investment governance, whereby the fund owner (the client) is the principal and the asset management firm is the agent. Asset management firms exhibit a broad range of organisational structures intended to convey to teams in charge of managing clients' portfolios medium- to long-term investment themes and key risk positions, thus ensuring consistency across portfolios and a proper share of responsibilities between staff and firms' senior management. These approaches do not usually involve the creation of additional benchmarks, expressing active positioning versus clients' benchmark, but rather envisage an important top-down component within the investment process.

One reason for the difference between the standard industry approach and that adopted by a sizeable portion of the central bank community may be found in the wide hierarchical gap, typical of central banks, between the principal (the board) and the agent (staff dedicated to portfolio management and risk control). Such a gap invites a direct involvement of senior management in the risk-taking process, with a clear attribution of responsibilities and measurable results, that tactical benchmarking are able to facilitate. In addition, a three-layer framework may improve central bank management's awareness of risk exposures stemming from active reserve management operations (including why they arise and their potential consequences[25]). Last but not least, central banks' investment public utility function is quite specific and distinct from traditional risk/return paradigms, as it is characterised by the crucial importance of safety/liquidity objectives and also by particular aversion to reputational risk. It may be argued that the direct involvement of senior management in active positioning may, through their closer association with these key objectives, help ensure that decisions remain consistent with a central bank's public utility function.

Due to the lack of relevant public statistics, it is impossible to formulate a broad-based assessment on whether the intermediate level really provides – in general and in the long term – value-added to active reserve management, increased total excess return and strategic asset allocation. Though the two-layer framework is simpler, should the intermediate level come at a cost (ie a negative contribution of the tactical positioning to total excess return), this may be acceptable to a central bank in so far as it helps allocate responsibilities consistently within its hierarchical structure.

Despite the absence of extra-return statistics on the tactical layer, it is still worth considering whether this level of the active investment process may suffer from its hybrid nature. Due to its time horizon, neither typical long-term oriented strategic asset allocation tools, nor the approaches normally supporting day-to-day portfolio management strategies, would adequately fulfill the needs of the tactical level. Unlike strategic decisions, medium-term investment choices seem particularly exposed to episodes triggering violent but short-lived market movements; such episodes can generate noise at the time of tactical decision-making processes and also create the need for a position management that is not in line with the medium-term horizon. In addition, a broad range of tools is available for processing information supporting strategic asset allocation as well as short-term trading. However, there are fewer instruments at hand for intermediate time horizons. This brief outline seems, to some extent, reflected by the heterogeneity of approaches adopted by central banks in their tactical allocation frameworks.[26]

Returning to the toolbox enhancements proposed above, there are several reasons the scorecard approach incorporating the model-based indicator on yields – while adaptable to any active management – may be well suited to the tactical level.

---

[25] In IMF (2013), it is highlighted that "Reserve managers, including their top management, should be aware of and be able to account for potential financial losses and other consequences of the risk exposures they are prepared to accept. Active management based on expectation of movements in interest rates or exchange rates, or a choice by the reserve management entity to accept a higher risk tolerance in its benchmark portfolios, requires that management is able to monitor and control any cumulative financial losses". Such need for awareness is probably more pronounced in central banks, compared to asset management firms, as the former are "multi-product" industries where senior and top management are not dedicated to the investment function, but rather deeply involved in crucial, institutional functions.

[26] See Table 4.

On the one hand, the multifactor quantitative indicator provides a clear signal based on a strictly empirical analysis of several macroeconomic and sentiment variables. On the other, the scorecard seems consistent with the collegial nature of investment committees, as the choice among a set of eligible input data and flexible weights allows for committee members to reach a consensus upon the selected variables and their relative importance. Furthermore, there is a fair degree of consistency between the monthly/quarterly time horizon of tactical decision-making and the typical frequency of scorecard inputs. All such factors underline the value-added of a tool that minimises subjectivity, supports synthesis and provides precise operational guidance

6. Concluding remarks

This paper seeks to enlarge the toolbox available for active reserve managers focusing on a widespread need – within the central bank community – for a decision-making process that takes proper account of quantitative as well as qualitative factors.

On the quantitative side, the starting point is a linear affine model incorporating sentiment and macro-economic variables, which allows for the exploitation of the predictable component (if any) embodied in term premia. Among the principal findings, it is worth highlighting that while the first three principal components explain about 99% of the variance of the yield change, the other two components may also add value. A further increase in its predictive power seems to be attainable by including a sentiment indicator among the explanatory variables. A simple and intuitive indicator (MQI) of long and short duration positioning is drawn from the expected excess return produced by the model. In principle, the model alone may be considered a useful tool for portfolio managers and decision-makers involved in active investment. However, some of the features typically characterising a central bank's investment process suggest a need for further development.

Reliance on purely quantitative indicators would enhance the automated nature of the decision-making process, but in ways that may not be fully consistent with a central bank's obligation to be highly accountable in its management of public funds, especially in conditions of high market uncertainty. On the other hand, the subjectivity intrinsic to purely qualitative assessments, and the bias that may arise from personal opinions or behavioural elements, argue for structured processes, if possible, blending quantitative and qualitative indicators and also fostering a balanced consensus within the context of collegial decision-making.

Scorecards and scoring systems for evaluating macroeconomic and financial information are nothing new, but the enhanced version developed in this paper contains some very specific elements: besides properly weighted macroeconomic and financial consensus variables, the scorecard also incorporates the MQI, whose weight can be calibrated also according to the desired balance between quantitative and qualitative factors. The final output is a more robust and comprehensive positioning indicator, compared to a "standalone" quantitative approach, particularly suitable for medium-term horizons.

Finally, with a view to accommodating this tool within central bank investment governance, some remarks are formulated with respect to a particular layer of the investment process specific to certain central banks – the so-called tactical level. It is contended that the hybrid nature of this level, in terms of both time horizon and objective function, may involve some weaknesses and require specific tools in support of decision-making. The enhanced scorecard seems an appropriate response to the need for combining a wide range of highly diversified quantitative and qualitative inputs on medium-term horizons, promoting synthesis and discussion among committee members.

Acknowledgements

The authors would like to express their gratitude to Giuseppe Reale[27] for his valuable suggestions to this article, especially those relating to the econometric section and the implementation tool.

References

Adrian T., Crump R.K. and E. Moench (2013), "Pricing the term structure with linear regressions", Journal of Financial Economics, pp. 110–138.

BIS (May 2009) "Issues in the governance of central banks".

BIS (2013) "Organisation of financial risk management at central banks".

Campbell, J. Y. and T. B. Thompson (2008). "Predicting the equity premium out of sample: can anything beat the historical average?" Review of Financial Studies 21: 1509-1531.

Chen, R.R. and L. Scott (1993), "Maximum likelihood estimation for a multi-factor equilibrium model of the term structure of interest rates", Journal of Fixed Income, 3, pp. 14–31.

Cellai, G. and Potente, F. "The scarcity of global safe assets", RBS Reserve Management Trends, 2013.

Cochrane, J. and M. Piazzesi (2005), "Bond risk premia", American Economic Review, 95, pp.138–160.

Cochrane, J. and M. Piazzesi (2008), "Decomposing the yield curve", Unpublished working paper, University of Chicago, Chicago, IL.

Collin-Dufresne, P. and R.S. Goldstein, (2002) "Do bonds span the fixed income markets? Theory and evidence for unspanned stochastic volatility", Journal of Finance, 57, pp. 1685–1730.

Dai, Q. and K. J. Singleton (2000), "Specification analysis of affine term structure models" Journal of Finance, 55, pp.1943–1978.

Duffee, G. (2002), "Term premia and interest rate forecasts in affine models", Journal of Finance, 57, pp. 405–443.

Duffee, G., (2010), "Sharpe ratios in term structure models", Unpublished Working Paper, 575, Johns Hopkins University, Baltimore, MD.

Duffee, G.R., (2011), "Information in (and not in) the term structure", Review of Financial Studies, 24, pp. 2895–2934.

Duffie, D., R. Kan (1996), "A yield-factor model of interest rates", Mathematical Finance, 6, pp. 379–406.

Engelbert J. Mayer, M. and J. Zechner (2013), "Sovereign Bond Risk Premia".

Ferreira, M. A. and P.Santa-Clara (2011). "Forecasting stock market returns: the sum of the parts is more than the whole." Journal of Financial Economics 100: 514-537.

Filipovi´c D., Larsson M. and A. Trolle (2014), "Linear-Rational Term Structure Models", Swiss Finance Institute, Research Paper Series, N°14-15.

Garbade K. D. (1986), "Models of Fluctuations in Bond Yields: an Analysis of Principal Components",

Garbade, K., (1996), Fixed Income Analytics, MIT Press, Cambridge, MA.

Greene, William H. (2011), Econometric Analysis http://pages.stern.nyu.edu/~wgreene/Text/econometricanalysis.htm

Gurkaynak, R.S., B. Sack, J.H. Wright, (2007), "The US treasury yield curve: 1961 to the present", Journal of Monetary Economics, 54, pp. 2291–2304.

Hamilton, J.D. and C. Wu, (2014), "Testable implications of affine term structure models". Journal of Econometrics, forthcoming.

Hendershott, T C.M. Jones, A.J. Menkveld (2011), "Does Algorithmic Trading Improve Market Liquidity ? " Journal of Finance.

HSBC Reserve Management Trends, 2014

Ilmanen A. (1995), Understanding the Yield Curve, volume 1-7.

Ilmanen, A. and R. Iwanowsky (1997), Dynamics of the Shape of the Yield Curve.

Ilmanen A. (2003), Time-varying Expected Returns in International Bond Markets.

Ilmanen A. (2005), A framework for analyzing yield-curve trades.

IMF – Revised Guidelines for Foreign Exchange Reserve management, 2013 – Discussion

Joslin, S.,Priebsch, M. and K.J. Singleton (2012), Risk premiums in dynamic term structure models with unspanned macro risks, Unpublished working paper.

Joslin, S., Singleton,K.J., and H. Zhu (2011), A new perspective on Gaussian dynamic term structure models, Review of Financial Studies, 24, pp. 926–970.

Kim, D.H.,Wright,J.H., (2005), "An arbitrage-free three-factor term structure model and the recent behavior of long-term yields and distant-horizon forward rates", Finance and Economics Discussion Series 2005-33, Board of Governors of the Federal Reserve System, Washington, DC.

Ludvingson, S. C. and S. Ng (2009), "Macro Factors in Bond Risk Premia", Review of Financial Studies, 22, pp. 5027–5067.

Mijatovic A. and P. Schneider (2013), Empirical Asset Pricing with Nonlinear Risk Premia, mimeo.

Moench, E., (2008), Forecasting the yield curve in a data-rich environment: a no-arbitrage factor-augmented VAR approach, Journal of Econometrics, 146, pp.26–43.

Piazzesi, M. (2003) "Affine term structure models", In Ait-Sahalia,Y., Hansen, L.P. (Eds.), Handbook of Financial Econometrics, vol.1., Elsevier,

[27] Banca d'Italia, Financial Investment Directorate.

Amsterdam, Netherlands, pp.691–758.

Sangvinatsos, A., and J. A. Wachter, (2005), Does the failure of the expectations hypothesis matter for long-term investors?, *Journal of Finance* 60, 179-230.

Scheinkman, J.A. and R. Litterman (1991), "Common factors affecting bond returns", Journal of Fixed Income, 1, pp. 54–61.

Singleton, K.J. (2006), Empirical Dynamic Asset Pricing, Princeton University Press, Princeton, NJ.

Timmermann A. (2006), "Forecast combinations", Handbook of Economic Forecasting Volume 1, 2006, pp. 135–196.

Trolle, A. B. and E. S. Schwartz (2013). The swaption cube. Working paper, Ecole Polytechnique Federale de Lausanne, Swiss Finance Institute, and UCLA, forthcoming in Review of Financial Studies.

Trolle, A. B. and E. S. Schwartz (2009). A general stochastic volatility model for the pricing of interest rate derivatives. Review of Financial Studies 22, 2007– 2057.

US Securities and Exchange Commission, Division of Investment Management "Guidance Update – Risk Management in changing fixed income market conditions", January 2014.

Wright,J.H. (2011), "Term premia and inflation uncertainty: empirical evidence from an international panel dataset", American Economic Review, 101, pp. 1514–1534.

Wyman, O. (2012) "The Volcker Rule restrictions on proprietary trading – Implications for market liquidity".