On the Impact of Tail Risk on the Yield Curve and the Response of Pension Funds: Evidence from the UK

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Abstract

We develop a Gaussian affine term structure model which accounts for the time-variant aggregate equity tail risk, to quantify the contribution of tail risk for predicting the UK government bond returns and its impact for bond pricing across certain maturities in a term structure model. We find that tail risk is a significant and robust predictor of the excess returns of short- to medium-maturity bonds in UK. Its impact on bond returns is consistent with flight-to-safety due to increased stress conditions in the equity market. We show that it is the rebalancing of UK's pension funds bond portfolios as a response to significant changes in tail risk that affects, in part, the yield curve via its impact on its unobserved constituent factors. Specifically, shocks to tail risk result in excess demand for medium-term bonds by UK pension funds, shifting the yield curve downwards, increasing its convexity and steepening its slope.

Keywords: Bond return predictability, equity tail risk, bond risk premium, flight-to-safety, structural VAR, Affine term structure models, pension funds

JEL Classification: G12, G14, E43, E44

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1. Introduction

The aim of this study is to quantify the contribution of the aggregate equity tail risk for predicting the UK government bond returns and its impact for bond pricing across certain maturities in a term structure model. We also seek to identify the causes for such impact. To this purpose we test whether fluctuating tail risk induces bond portfolio rebalancing by UK pension funds and if this adjustment alone has a measurable impact on UK's term structure. Tail risk may be broadly defined as the likelihood of greater than expected asset price movements; typically, more than two or three standard deviations away from the mean of the returns' distribution. A growing literature suggests a significant link between tail risk and asset values. For example, Ang et al. (2006), Andersen et al. (2019), Kelly and Jiang (2014), Bali et al. (2009), and Bollerslev and Todorov (2011) show that stock returns reflect a premium for tail risk, while Buraschi et al. (2014), Brown et al. (2012), Agarwal et al. (2017), Agarwal et al. (2009), and Karagiannis and Tolikas (2019) present evidence that tail risk may help to explain fund returns. Yet, the impact of aggregate equity tail risk on bond yields remains unsettled and largely unexplored and this serves as the main motivation of our study.

The unpredictable incidents of very significant losses in the values of assets during tail risk events, may often lead to cascades of liquidations in the asset management industry (Coval and Stafford, 2007; Shleifer and Vishny, 2011; Ellul et al., 2011); this is especially the case for pension funds which are subject to fixed payments obligations and risk tolerance constraints. To adjust the market risk of their portfolios at their previously desired level, funds faced suddenly with severely adverse market conditions, are required to incur dead-weight costs. Typically, they first attempt to reduce risk by liquidating their most liquid assets that can be traded at the lowest possible spreads, minimising transactions costs. The consequence of this strategy is a resulting portfolio overloaded with illiquid assets. If these conditions last longer than anticipated, the already reduced liquidity of their portfolios all but disappears, leading funds to suffer additional costs to reduce risks further, amplifying the dead-weight adjustment costs as the price of liquidity soars.[1] The impact of tail risk events on portfolio value is, therefore, particularly important for pension funds whose return path is critical to deliver a-priori agreed fixed obligations.

Aware of the potential impact of tail risk on their portfolios, fund managers attempt to minimise its impact whilst avoiding the high costs of carry associated with conventional hedges in either the derivatives or cash markets.[2] Indeed, it is well documented in the literature that in times of increasing financial distress in equity markets, fund managers, to protect the value and liquidity of their portfolios, opt *en-masse* to disengage from high yielding risky assets for highly liquid and default-free assets; the literature refers to episodes of such collective action of asset substitution as Flight-to-Safety (FTS).[3] There is a lively literature in financial theory accounting for and predicting such phenomena that suggests a potentially significant link between tail risk and FTS episodes. In Vayano's (2004) model, risk averse investment managers worrying about the value to be realised from immediate

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[1] When illiquid assets trade at fire-sale prices, hoarding liquidity is particularly profitable (Allen and Gale, 2004; Diamond and Rajan, 2011; Gale and Yorulmazer, 2013; Malherbe, 2014). Thus, both hedging and/or speculative demand for liquidity can justify a lower yield for liquid assets (Vayanos and Vila, 1999).

[2] Option type hedging strategies require substantial cash advances whilst hedging positions based on implied volatility will not deliver the required returns computed under the most frequent market conditions given their fixed obligations.

[3] Baele et al. (2020) define as FTS an episode that satisfies the following three criteria: (i) simultaneous low equity and high bond returns, (ii) a highly volatile equity market, and (iii) a negative high frequency correlation between the equity and bond markets. Baele et al. (2020) note that stock and bond returns are likely positively correlated outside the FTS periods as both represent high duration assets. Negative aggregate demand shocks may also entail negative stock-bond return correlations but will only be identified as FTS when accompanied by substantial market stress. The most recent example of this phenomenon is the 2008 world-wide economic and financial crisis, when investors experienced acute losses on multiple asset classes in their portfolios that could not be compensated by the price movements of other assets.

required redemptions during high volatility periods, a typical pension fund situation, will opt FTS. In Caballero and Krishnamurthy (2008), uncertainty stemming from the incomplete knowledge of the returns' distribution left tail, will lead fund managers to sell with some urgency risky assets in favour of non-contingent and default-free assets traded in deep markets, when aggregate liquidity in the equity market is low, thereby provoking an FTS. Brunnermeier and Pedersen (2009) study a model in which speculators, who provide market liquidity, have margin requirements increasing in volatility, which can help cause a liquidity spiral following a tail event, that may lead to an FTS as liquidity deteriorates in all markets.[4]

FTS episodes, also give valid reasons to study the nature of the relation between the returns on government bonds and stocks, under conditions of changing tail risk. Indeed, although these two assets can be considered as complementary under normal circumstances, with institutional investors, typically, holding fixed proportions of bonds and stocks, FTS episodes suggest that under turbulent circumstances investors treat them as substitutes. There is accumulating evidence of the existence of bond pricing factors generated in the equity markets. Connolly et al. (2005) and Baele et al. (2010) show that measures linked to the stock market's uncertainty have considerable explanatory power for the time variation in the stock-bond return relation and important cross-market pricing effects. Crump and Gospodinov (2019) report that equity tail risk has strong in-sample predictive power for future US Treasury bond returns. Within the international context, Baele et al. (2020) provide evidence of FTS episodes from stock to bond markets, using data for 23 countries. Such FTS

[4] Regarding the underlying motives behind such actions two studies emphasize the importance investors place on securing liquidity. First, the study by Longstaff (2004) using US bond price data calculates that the liquidity premium in Treasury bonds accounts for up to 15% of their value. Second, Beber et al. (2009) using data from the Euro-zone sovereign bond market, report that in times of increased volatility in the equity market, investors seek to secure liquidity rather than asset quality.

episodes, therefore, motivate the study of the relation between bond returns and the aggregate equity market tail risk.

In this study we examine whether the asset allocation decisions of UK pension funds triggered by changes in the level of the aggregate equity tail risk are reflected in the changes of the term structure of interest rates of the UK government securities. Specifically, we address the following two questions: (i) Does the aggregate equity tail risk have an effect on the UK bond risk premia? and (ii) Does the asset allocation decisions of the UK pension funds, triggered by changes in the level of aggregate equity tail risk, have an impact on the term structure of the UK government securities? To the best of our knowledge, this is the first study focusing on the impact of the aggregate equity tail risk on the UK bond market and the impact of the actions of pension fund managers facing changes in the level of the aggregate equity tail risk on the term structure of interest rates. We use the daily returns of the FTSE All Share index over the period January 1992 to December 2017, to estimate the aggregate equity tail risk of the UK stock market. In particular, we employ a time-variant measure of aggregate equity tail risk developed by Kelly and Jiang (2014), based on the common fluctuations in tail risk in the cross-section of individual stocks. With respect to the analysis related to the UK term structure of interest rates, we decompose bond yields into expectations of future short rates (averaged over the lifetime of the bonds) and term premia (i.e., the additional returns required by investors for bearing the risk of long-term commitment). For that reason, we use Gaussian affine term structure models, a methodology that relies primarily on accounting for yields and returns based on the calculation of unobserved risk factors representing combinations of yields across maturities (Duffee, 2002; Kim and Wright, 2005; and Abrahams et al., 2016). We also incorporate the unobserved risk factors derived from the decomposition methodology of Litterman and Scheinkman (1991), as well as additional information reflecting the overall economic environment, a significant predictor as reported by Ioannidis and Kook (2021).[5]

We find that tail risk makes a significant and independent contribution in the predictability of excess returns of the UK government bonds across certain medium maturities (i.e., 2-10 years). For example, the inclusion of tail risk in a variety of linear models involving the three and five principal components of UK excess bond returns leads to a significant reduction in prediction error variance in a variety of in- and out-of-sample forecasting exercises. Subsequently we ascertain the behavioural causes for such findings by focusing on the financial decisions of a substantial class of financial institutions operating in the UK bond market, namely UK pension funds. We find that the rebalancing of UK pension funds bond portfolios triggered by significant changes in tail risk affects, in part, the yield curve via its impact on its unobserved constituent factors. Specifically, shocks to tail risk result in excess demand for medium-term bonds by UK pension funds, shifting the yield curve downwards, increasing its convexity and steepening its slope. These results account for our previous findings related to the importance of tail risk as a predictor of the excess returns of medium-term bonds.

Our study makes a number of contributions. First, we contribute to the related literature by offering new insights into the impact of the aggregate equity tail risk on bond yields and the asset allocation of the UK pension funds. Second, we provide substantial empirical evidence that changes in the level of equity tail risk have significant pricing effects on bonds of short to medium maturities. Third, and this is the first study of its kind, we provide

[5] Rudebusch et al (2004) pioneered this approach by using a similar model for the US term structure augmented by a number of macroeconomic factors such as output, growth, and inflation.

a behavioural explanation for the observed impact of tail risk of the UK bond market. Specifically, we show that changes in the level of equity tail risk trigger reallocation of the pension fund portfolios which in turn have a significant impact on the constituent factors of the term structure.

The paper is organised as follows. Section 2 provides details about our dataset and a statistical description of our sample. Section 3 provides an exposition of the methodology used for the estimation of the aggregate equity tail risk, and the term structure decomposition and the formulation of arbitrage-free affine models. Section 4 presents our empirical results related to the independent contribution of our measure of tail risk to the UK's bond excess returns across different maturities. Section 5 details the development and estimation of a structural VAR that relates tail risk to the pension funds' bond portfolio re-arrangements and subsequently to the factors of the term structure. Conclusions are presented in Section 6.

2. Data and Sample Description

The sample we use to estimate the aggregate equity tail risk of the UK stock market consist of all shares that make up the FTSE All Share index over the period January 1990 to December 2017.[6] During our sample period, the number of index constituents averaged 678 stocks each month, with a minimum of 600 (May 2013) and a maximum of 852 (August 1998). That number of stocks implies an average pool of around 15,000 daily returns per month, of which the lowest 5% is used in the calculation of our tail risk estimate. This is an average number of

[6] The FTSE All Share is a market capitalisation weighted index comprising around 600 shares of the more than 2,000 shares traded in the London Stock Exchange (LSE). The index aims to cover at least 98% of the total capital value of all the UK companies eligible for inclusion (i.e., around £2.6 trillion by end of 2017).

about 750 daily returns per month which is sufficiently high to allow for sound statistical estimation of the aggregate equity tail risk on a monthly frequency. Figure 1 shows the daily returns of the FTSE All Share price index during the time period covered by our sample. The figure shows the volatile time periods related to the early 90s (Iraqi invasion to Kuwait, collapse of asset prices in Japan, Black Wednesday), the Russian default and the collapse of the LTCM in 1998, the 9/11, the Credit crunch in 2008-2009, the European sovereign crisis in 2010-2012, and the 2016 Brexit referendum.

Insert Figure 1 around here

The data on UK interest rates we employ in our analysis are obtained from the Bank of England (BoE).[7] We estimate our Gaussian affine term structure model using month-end zero coupon yields. The pricing factors are the principal components extracted from the bond yields with maturities of 12, 24, 36 ,60, 84, 120, 180, and 240 months. For the short rate we use the one-month interest rate quoted by the BoE and we also calculate the excess returns for holding periods of one and six months. The BoE constructs the yields with maturities of six months and longer using the smoothed cubic spline method of Anderson and Sleath (2001). As in Joyce et al. (2010), Malik and Meldrum (2016), Kaminska et al. (2018), and Levant and Ma (2016), our sample starts in October 1992, when the UK adopted an inflation target framework for monetary policy, ends in December 2017, and includes 303 monthly observations.

The UK pension fund data are collected from the Office of National Statistics (ONS) and includes quarterly net investment and acquisitions figures related to the UK self-

[7] https://www.bankofengland.co.uk/statistics/yield-curves.

administered pension funds financial transactions in government bonds.[8] ONS defines net investments to be the difference between levels of acquisitions and disposals of assets by pension funds, and acquisitions as the procurement of assets (i.e., gilts and shares). All data are reported at current prices. Table 1 reports summary statistics of our pension fund data grouped into short/medium-term (i.e., less than 15 years) and long-term maturities (i.e., greater than 15 years). The figures reveal a net investment preference of pension funds for government bonds of long maturity with a total net investment of over half a trillion GBP, and disinvestment from short and medium maturity bonds as indicated by a negative total net investment of 14 billion GBP. UK pension funds tend to procure more short and medium maturity bonds as opposed to long maturity government bonds; indeed, the acquisitions of short and medium bonds by pension funds total a value of over 815 billion GBP as opposed to 746 billion GBP for bonds of longer maturity.

Insert Table 1 around here

Lastly, to measure the policy related economic uncertainty in UK, we use the Economic Policy Uncertainty (EPU) index developed by Baker et al. (2016).[9] The construction of the EPU index is based on the number of articles published by 11 leading UK newspapers that contain the terms 'uncertain', 'uncertainty', 'economic', or 'economy', as well as the policy relevant terms 'policy', 'tax', 'spending', 'regulation', 'Bank of England', 'budget', and 'deficit'. We collect monthly data for the UK EPU index for the time period from January 1992 to December

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[8] https://www.ons.gov.uk/economy/investmentspensionsandtrusts/datasets/mq5investmentbyinsurancecompaniespensionfundsandtrusts

[9] The 11 UK newspapers include: *The Financial Times*, *The Times* and *Sunday Times*, *The Telegraph*, *The Daily Mail*, *The Daily Express*, *The Guardian*, *The Mirror*, *The Northern Echo*, *The Evening Standard*, and *The Sun*.

2017.[10] Although the index mainly considers economic uncertainty stemming from uncertainty related to government policies, it has been shown that it is closely related to both macroeconomic and financial variables (e.g., Aastveit et al., 2017; Karnizova et al., 2014; Bordo et al., 2016). The monthly data for the period January 1992 until January 1997 is annual data interpolated from historical EPU UK data. The level of the UK EPU index on a monthly frequency from January 1992 to December 2017 is shown in Figure 2. Apparently, the index increases during periods of major economic and political events like the UK pound withdrawal from the European Exchange Rate Mechanism, the collapse of LTCM in 1998 and the turmoil that followed in the financial markets, the 9/11, the Credit crunch in 2008-09, the European sovereign crisis in 2010-2012, and spikes after the 2016 Brexit referendum.

Insert Figure 2 about here

3. Methodology

This section describes the measurement of the aggregate equity tail risk we adopt in our study, and the approach we use to decompose the term structure of interest rates in UK.

3.1 The aggregate equity tail risk

To proxy for the aggregate equity tail risk, we use the measure developed by Kelly and Jiang (2014). This is a time-varying measure of tail risk derived directly from the cross-section of stock returns. This approach describes the lower tail returns with the probability condition below:

$$Pr\,ob\left(R_{i,t+1} < r \middle| R_{i,t+1} < u_t, and\ I_t\right) = \left(\frac{r}{u_t}\right)^{\frac{-\alpha_i}{\lambda_t}} \tag{1}$$

[10] Data for the EPU index are collected from the https://www.policyuncertainty.com website maintained by Baker et al. (2016).

where $R_{i,t+1}$ is the return of stock *i* at time *t*+1 that is less than one of the lower quantiles of the cross-sectional distribution of returns, denoted by u_t $(r < u_t < 0)$, and I_t is the information set available at time t. Although there is no set rule for selecting the threshold, we follow the theoretical rule of Gabaix, Gopikrishnan, and Plerou (2006) and the empirical evidence in Karagiannis and Tolikas (2019) and Kelly and Jiang (2014), and we set u_t equal to the 5th percentile of the cross-sectional distribution of the stocks' returns at time t.[11] Thus, we effectively use the lower 5% of the cross-sectional daily returns of all FTSE All Share stocks in our sample to estimate the aggregate tail risk λt on a month-by-month basis. The time varying nature of our tail risk estimator implies that its actual value varies as the volatility of the cross-sectional distribution of returns varies on a period-by-period. Thus, the measure of aggregate equity tail risk we adopt in our study accounts for commonality of tail risk across the individual stocks in our sample. The tail exponent a_i/λ_t determines the shape of the tail of the cross-sectional distribution of the stock returns; the higher the tail risk measure λ_t, the fatter the lower tail of returns, and vice versa. Also, individual stocks are allowed to have different idiosyncratic tail risks, determined by the parameter α_i, but their common tail risk dynamics are determined by a single process across all stocks, determined by the parameter λ_t. To estimate the common tail risk λ_t on a month-by-month basis, we pool the daily cross-sectional returns of all stocks in the FTSE All Share index for each month and calculate the Hill power law estimator:

$$\lambda_t^{Hill} = \frac{1}{K_t}\sum_{k=1}^{K_t}\left[ln\left(R_{k,t}\right) - ln(u_t)\right] \qquad (2)$$

[11] Gabaix, Gopikrishnan, and Plerou (2006) suggest setting the probability of exceeding *u* at 5%, while Karagiannis and Tolikas (2019) and Kelly and Jiang (2014) report that ranging the fixed percentile from 1% to 5% leads to similar empirical results.

where $R_{k,t}$ is the k^{th} daily stock return that is lower than the threshold u_t in month t, and K_t is the total number of the cross-sectional returns below the threshold u_t within month t. Figure 3 shows the tail risk estimates (standardised) from January 1992 to December 2017. The correlation coefficient between the aggregate tail risk and the one-month subsequent monthly return of the FTSE All Share index is 0.42 and is statistically significant at the 1% level, which indicates that tail risk is an important driver of the FTSE All Share returns.

Insert Figure 3 about here

3.2 Modelling bond yields as affine functions of risk factors

In this section we present a brief outline of the empirical methodology linking the observed term structure of interest rates to a set of observed and unobserved factors. We use the conventional macro-finance framework to establish the nature of the relationship between various risk factors and the term structure of interest rates. Since Litterman and Scheinkman (1991), the finance literature summarises the term structure of interest rates into three latent factors, representing the level, slope, and curvature of the yield curve. To extract the three latent yield factors, we follow the approach of Diebold and Li (2006) who find that these three factors explain more than 90% of the entire movement in the term structure. They modify the Nelson and Siegel (1987) parsimonious exponential function form with time-varying parameters in a state space setting.[12] Adrian et al. (2013), ATSM thereafter, estimate a five factor model for the US, and Malik and Maldrum (2016) propose a four factor model to account for the evolution of the UK term structure. More recently, Ioannidis and Ka (2021)

[12] Unlike any other typical term structure model restricted with the no-arbitrage condition, the Nelson-Siegel model does not impose the no-arbitrage condition (Bjork and Christensen, 1999; Filipovic, 1999).

find that fluctuations in the Economic Policy Uncertainty (EPU) index of Baker et al. (2016) are strong predictors for the US excess bond returns (CP).[13]

The dynamic Nelson-Siegel (NS) yield curve model has the form below (Diebold et al., 2006; Diebold and Li, 2006):

$$y_t(n) = l_t + s_t\left(\frac{1-e^{-\gamma n}}{\gamma n}\right) + c_t\left(\frac{1-e^{-\gamma n}}{\gamma n} - e^{-\gamma n}\right) \tag{3}$$

where $y_t(n)$ is the predicted yield at each time period t with n months to maturity, and l_t, s_t, and c_t are time varying coefficients to be estimated, which can be interpreted as the level, slope, and curvature of the yield curve, respectively. Specifically, l_t represents the level of the long-term interest rate; a positive (negative) s_t represents an upward (downward) sloping yield curve, and a positive (negative) c_t generates a hump (trough) in the yield curve. And $\gamma(> 0)$ is a parameter that controls for the exponential decay rate of the slope and curvature coefficients; thus, it determines both the steepness of the slope and the location of the maximum of the yield function. We can rewrite this state-space system in a matrix form as:

$$\begin{aligned} (\boldsymbol{f_t} - \boldsymbol{\mu}) &= \boldsymbol{A}(\boldsymbol{f_{t-1}} - \boldsymbol{\mu}) + \boldsymbol{\eta_t} \\ \boldsymbol{y_t}(\boldsymbol{n}) &= \boldsymbol{\Gamma} \boldsymbol{f_t} + \boldsymbol{\varepsilon_t}(\boldsymbol{n}) \end{aligned} \tag{4}$$

where $\boldsymbol{A}$ and $\boldsymbol{\Gamma}$ denote the factor transition and factor loadings matrices, respectively, and $\boldsymbol{f}$ denotes the factors, both observed and unobserved. The factor disturbances, $\boldsymbol{\eta_t}$, are allowed to be correlated, but we impose a restriction of cross-sectional independence with

[13] Ioannidis and Ka (2021) report results that imply that the EPU has strong predictive power for future return that is not spanned by the information conveyed by the current yield curve. They also find that the EPU is a return predictor that is independent from other well-known forecasting factors used in the literature (e.g., Cochrane and Piazzesi, 2005; Cieslak and Povala, 2015). They also report that their results remain robust after controlling for other measures of macroeconomic and financial uncertainty as suggested by Jurado et al. (2015). Ludvigson and Ng (2009), and Ludvigson et al. (2015). Further, they report that the predictive power of EPU is more closely related to bond price volatility at higher frequencies but is almost disappears for investment horizons longer than six months. For example, they find that a one standard deviation increase in the US EPU predicts a positive excess return for the US treasury return from 0.48% (one year, annualised) to 1.97% (five year) over a one month holding period.

the observation equation disturbances, $\boldsymbol{\varepsilon_t}$, resulting in a diagonal covariance matrix, $\boldsymbol{H}$, implying that the deviations of the observed interest rates from the estimated yield curve are uncorrelated.

Assuming that *K* risk factors affect bond prices, the arbitrage-free affine term structure model, begins by assuming that the time evolution of the risk factors can be adequately described by a simple VAR(1) of the form:

$$f_{t+1} = F + \Phi f_t + \eta_{t+1} \tag{5}$$

where *F* denotes a vector of constants and *Φ* is the matrix of coefficients to be estimated, under the assumption that shocks to the factors, η, follow a multivariate normal distribution with zero mean and *Σ* variance ($\eta_{t+1} \sim N(0, \Sigma)$).

Further, the assumption of arbitrage-free pricing implies the existence of a pricing kernel, M_{t+1}, that satisfies the bond prices, $P_t^{(n)}$, of a given maturity (n) as:

$$P_t^{(n)} = E_t(M_{t+1} P_{t+1}^{n-1}) \tag{6}$$

Following Duffie (2002), the pricing kernel M_{t+1}, can be expressed as:

$$M_{t+1} = exp(-i_t - \tfrac{1}{2}\lambda_t' \lambda_t - \lambda_t' \sum -0.5\, \eta_{t+1}) \tag{7}$$

where i denotes the short-term instantaneous interest rate, $i_t = \theta_0 + \theta_1' f_t = -ln(P_t^1)$,

and λ_t denoted the time dependent price of risk expressed as:

$$\lambda_t = \Sigma^{-0.5}(\lambda_0 + \lambda_1 f_t) \tag{8}$$

Subsequently the arbitrage-free price of a default risk-free bond of maturity (n) can be written as:

$$P_t^n = exp(A_n + B_n' f_t) \tag{9}$$

the matrices A_n and B_n denote the factor loadings and for each maturity they are determined by the recursions:

$$A_{n+1} = -\theta_0 + A_n + B_n'(f - \Sigma\lambda_0) + 0.5(B_n'\Sigma\Sigma' B_n), \tag{10}$$

$$B_{n+1} = (\Phi - \Sigma\lambda_1)' B_n - \theta_0, \tag{11}$$

From equation 9, it follows that $y_t^n = -\frac{ln(P_t^n)}{n} = \alpha_n + \beta_n' f_t$ (12)

Following Adrian et al. (2013), we model the excess returns, rx, as affine functions of the risk factors:

$$rx_{t+1}^{(n)} = lnP_{t+1}^{(n-1)} - lnP_t^{(n)} - i_t \tag{13}$$

under the assumption of multivariate normality for both shocks to the factors and bond returns, ATSM show that the expected returns for the one–period holding horizon for bonds of maturity (n) can be expressed as:

$$E_t[rx_{t+1}^{(n)}] = \beta_t^{(n)'}[\lambda_0 + \lambda_1 f_t] - \frac{1}{2} Var_t[rx_{t+1}^{(n)}] \tag{14}$$

where $\beta_t^{(n)'} = Cov[rx_{t+1}^{(n)}, \varepsilon_{t+1'}]\Sigma^{-1}$ (15)

Arbitrage free bond prices (equation 9) for bonds maturing at period (n), can been calculated using the recursions in equations 10 and 11. These can be used to compute excess bond returns for various maturities and the vectorised versions of equations 14 and 15 provide estimates of the 'expected excess returns' for bonds of different maturities.

The difference between the values computed from equation 13 and equation 14 represents the unanticipated component of the excess bond returns. To obtain estimates for the parameters we follow the three-stage procedure suggested by ATSM who use excess holding period returns to estimate the model. By splitting the estimation procedure into three-step linear regressions, ATSM eliminate problems associated with the computational complexity of the estimation.

4. Empirical Analysis and Results

In this section we proceed by testing for the effect of tail risk as an independent risk factor of the yields and excess returns of UK bonds. In the first instance, using the arbitrage–free decomposition methodology, we test for the statistical significance of the factor loadings associated with tail risk as an independent risk factor on both yields and excess returns. Subsequently, having extracted the risk factors, we test for the contribution of tail risk as an independent predictor of observed excess returns across different maturities for two holding periods.

4.1. Term structure decomposition: Factor loadings (excess returns)

Following the ATSM methodology of decomposing the yield curve and the excess returns into a number of factors, we present the factor loadings for two factor combinations. In the first combination, the factor set consists of the first five principal components (*PC*) of the term structure and tail risk, while the second combination includes the first three components (i.e., level, slope, and curvature), along with EPU and tail risk. Figures 4 and 5 depict the factor loadings for tail risk and the other factors along with the 95% confidence interval on excess returns for the first and second combination of factors, respectively.

Insert Figure 4 about here

Insert Figure 5 about here

In both combinations of factors, the loadings associated with tail risk are statistically significant at the 95% confidence level, albeit marginally so in the first model. Importantly, the tail risk factor takes on a statistically significant loading that it is independent of the EPU and the additional factors introduced by ASTM. As expected, tail risk has a negative impact on the term structure of the excess bond returns, and it is more pronounced on short to medium maturity bonds.

To establish further the relevance of equity tail risk in the presence of the five principal components, we subsequently estimate the expected excess returns for a number of selected maturities (i.e., 24-, 60-, 120-, and 230-months), with and without tail risk using equations 9-15. We then compare the estimated expected excess returns to the observed excess returns calculated using actual bond price data and find that the inclusion of tail risk to the five principal components results in stronger statistical association between the expected and observed returns, for short- to medium-term maturity bonds. Table 2 presents the correlation coefficients between the actual excess returns and the predicted excess returns from the two models; both models generate excess returns distributions with the same means and unequal variances. Although the sample variances from both models are considerably smaller in comparison to the observed excess returns, the variance calculated model including tail risk is significantly closer to the observed variance for short/medium-term maturities.

Overall, the impact of tail risk as an additional informational input to the five principal component model in the computation of expected excess returns is statistically significant, albeit modest and limited to the same maturities.

Insert Table 2 about here

4.2 Impact of tail risk on the excess returns of bonds

The evidence so far is supportive of the hypothesis that the aggregate equity tail risk is an independent principal component of bond excess returns for bonds of short- to medium-term maturities and that it helps to explain the observed variability of excess return. Motivated by our initial findings, this section tests for the independent contribution of tail risk to the determination of excess bond returns across all eight maturities we consider whilst varying the information set.

We first test for the predictive contribution of tail risk to excess returns for bonds whose maturities range from 1 to 20 years, for one- and six-month holding periods, in the context of three linear models that include either three or five factors, and EPU as an additional predictor. Our interest is in the establishment of the contribution of tail risk as an explanatory variable of bond excess returns, and for that reason we estimate the following three models:

Model 1 (M1): $xr_{i,t} = \sum_{j=1}^{3} \beta_i PC_{j,t} + \gamma_i^{'} Tail_t + u_{M1,t}$

Model 2 (M2) $xr_{i,t} = \sum_{j=1}^{5} \beta_i^{*} PC_{j,t} + \gamma_i^{''} Tail_t + u_{M2,t}$

Model 3 (M3) : $xr_{i,t} = \sum_{j=1}^{3} \beta_i^{+} PC_{j,t} + \gamma_i^{'''} Tail_t + \delta_i EPU_t + u_{M3,t}$

where $i = 1, \cdots, 20$ denotes maturity in years, xr denotes the bond excess returns, $Tail$ denotes tail risk, PC denotes the unobserved factors (i.e., three or five principal components) extracted from the decomposition of the cross-sectional structure of the term structure of the UK interest rates, EPU denotes Economic Policy Uncertainty, and $u_{M,t}$ denotes the stochastic component of excess returns. Conventionally, the three basic factors are the level, slope, and curvature (i.e., convexity), which we also augment by two additional factors following the methodology of ASTM.

Table 3 reports the estimated coefficients and *p*-values, with bootstrapped standard errors, of tail risk ($\gamma', \gamma'', \gamma'''$) in models M1, M2, and M3, respectively, and for a holding period of one month. The estimated coefficients indicate that tail risk makes a statistically significant contribution to the determination of excess returns for the one month holding period in all three models, and this is especially the case when coupled with EPU (i.e., M3). Further, its effect is more pronounced on short to medium maturity bonds in all three specifications. For example, when the tail risk factor is considered alongside the three principal components (M1), in the case of a three-year bond and for a holding period of one month, a one standard deviation increase in tail risk, leads to a reduction in the expected excess return from 0.12% to 0.04%. Further, when the tail risk factor is considered alongside the three principal components and EPU (M3), in the case of a three-year bond and for a holding period of one month, a one standard deviation increase in tail risk, leads to a reduction in the expected excess return from 0.11% to -0.01%, whilst the impact of the EPU is to increase this expected excess return by 0.14%.

Insert Table 3 about here

When we extend the holding period to six months, the contribution of tail risk to the determination of bond excess returns is far more pronounced. For example, in the case of a three-year bond, a one standard deviation increase in tail risk, leads to a reduction in the expected excess return from 0.71% to 0.41%, whilst the impact of the EPU is to increase this expected excess return by 0.25%. The results are presented in Table 4.

Insert Table 4 about here

This is a rather surprising result as no other such results have been reported in the literature, at least for the UK term structure. A likely explanation appears to be that rising tail risk provides strong incentives to some agents who have specifically dated liquidity requirements to avoid predicted cash shortfalls due to the fluctuating stock prices and choose to switch to short and medium maturity bonds, which are liquid, well in advance from the delivery of their cash obligations. A typical institution with this type of precisely dated liquid obligations is a pension fund.

We then test for the contribution of tail risk in predicting out-of-sample one period ahead (i.e., one month) excess bond returns by comparing the performance of various factor only based models to those including tail risk and EPU. Following Bower and Hamilton (2017) we analyse whether a model having tail risk as an additional factor leads to better out-of-sample predictive performance relative to its chosen benchmarks with three or five unobserved factors. For that reason, we divide our full sample into two parts, in- and out-of-sample, and make predictions recursively by extending the sample by one month consecutively. The performance of the out-of-sample predictions are assessed by the relative sizes of the models' mean-squared errors (*MSE*); one that includes the additional factors (i.e., tail risk and EPU), MSE^{AFM}, and the prediction errors of the chosen benchmark models, MSE^{BM}. We conduct the analysis and report the results for two different learning in-sample time periods. The first one, January 1992 to December 2007, excludes the financial crisis, while the second one, January 1992 to December 2012, includes the financial crisis and ends at the beginning of the recovery. The results in terms of the mean-squared errors ratios of the out-of-sample comparison of the monthly excess bond returns generated by the comparison models, together with the *p*-values of the Clark and West (2007) mean-squared forecasting error adjusted test for equal forecasting accuracy, are presented in Table 5.

Insert Table 5 about here

Independently of the in-sample period chosen, the weight of the evidence is that tail risk makes a statistically significant contribution to the out-of-sample predictability of excess bond returns. Indeed, it is striking that in the first in-sample analysis there is uniformly a marked and statistically significant improvement in prediction. As the in-sample period is extended to include the financial crisis, the contribution of tail risk becomes less pronounced, although in all cases adding tail risk to the five-factor model improves out-of-sample prediction for some maturities. Further, the addition of tail risk to the set of risk factors never reduces the model's predictive performance. Overall, out of the total of 48 cases presented in Table 5, models containing tail risk result in 23 cases of better forecasting out-of-sample performance, at the 10% level of significance.

The results of our analysis in this section clearly establish that the aggregate equity tail risk is a statistically significant determinant of the expected excess returns for short and medium maturity bonds in the UK for both one- and six-months holding periods. Our results complement Adrian et al. (2019), who report statistically significant predictability for forecast horizons of about five months and longer using the five-factor model. We confirm the strong predictive power of the equity tail risk factor for similar holding horizons compared to other studies that confirm predictability for only one-month excess bond returns. The evaluation of the out-of-sample forecasting contribution of tail risk is more problematic. The inclusion of the economic and financial crisis has mixed impact of the usefulness of tail risk. Whilst its own impact against the five factors is reduced, the combination of tail risk and EPU leads to a remarkable contribution to the out-sample prediction of excess returns for short and medium maturity bonds.

5. Pension Fund Bond Portfolio re-balancing and the Term Structure Model

The pension fund industry is an interesting field to conduct an exercise that will allow us to examine the impact of tail risk on bond portfolio rebalancing and its subsequent impact on the term structure of interest rates in UK.[14] Pension funds can be thought of as financial entities whose portfolios consist of 'short' and 'long' bonds of various maturities along with equity; following ONS convention, we consider 'short' bonds whose maturity does not exceed 15 years. Their risk appetite is controlled by regulation and supervisory boards that put limits in the risk profile of their overall financial wealth. The UK pension fund industry is facing an unprecedented demographic challenge which in an economy with low yields has led to underfunding pressures for most of the pension schemes, with liabilities' growth for the first time exceeding assets' growth.[15] For example, by end-March 2017 total liabilities of UK pension schemes (i.e. £1.7 trillion) outstripped total assets by £162 billion, with the former accounting for almost 85% of the UK GDP in 2017 (i.e. £2.0 trillion) (PPF Purple Book, 2017). The increasing underfunding pressure faced by the UK pension schemes have put pension funds under substantial pressure to achieve and maintain a high level of return for pension

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[14] Pension funds are portfolios of assets managed by professionals with the aim of serving the financial obligations established by pension schemes. Pension schemes are long-term social security saving tools aiming at providing income during retirement that complements the income from the state pension. Thus, pension funds can be thought of as the instrumentation of a single or several pension schemes.

[15] For example, PPF (2007) reports that in 2007 a 10 basis points increase or decrease in gilt yields increases or decreases, respectively, the end-March 2007 estimated aggregate scheme funding level (on an s179 valuation basis) by around £12 billion. Also, a 2.5% increase or decrease in equity prices increases or decreases, respectively, the aggregate scheme funding by around £12 billion. Further, a 7.5% fall in equity markets and a 0.3% fall in bond yields would result in a deficit of £21 billion compared with the end-March 2007 surplus of £52.9 billion. In addition, on the basis of the longevity assumption used in the s179 valuation, each year would add around 3% (i.e., £20-25 billion) to the aggregate pension scheme liabilities. For comparison, in 2017 a 10 basis points increase or decrease in gilt yields decreases or increases, respectively, the end-March 2017 aggregate deficit by £24.1 billion, while a 5% rise in equity prices would reduce the aggregate deficit by a similar amount. Further, an increase in life expectancy such that the experienced life expectancy is now equivalent to that of an individual two years younger, would increase aggregate scheme liabilities by 7.4%, or £125.5 billion. Note that these sensitivities do not take into account the use of derivative instruments to hedge changes in interest rates, inflation, equity levels, or longevity.

schemes to be able to provide the promised benefits to pensioners. Further, the closely related literature on the risk-taking behaviour of funds provides strong evidence that the underfunding pressures, may encourage pension fund managers to alter the susceptibility of the portfolios they manage to tail risk (e.g., Brown et al., 1996). Indeed, our prior analysis provides evidence of the impact of equity tail risk on the excess returns of 'short' maturity bonds. Specifically, we find that tail risk is a robust, independent predictor of excess returns in the presence of both the unobserved factors and EPU.

Although, there is some limited empirical literature on the composition of pension funds' portfolios in the UK, none of these studies examine the pension funds response to tail risk in the UK equity market where they hold most of their equity portfolios (e.g., Dinenis and Scott, 1993; McCarthy and Miles, 2013). To assess the impact of tail risk on the investment behaviour of UK pension funds and subsequently on the term structure of interest rates, we first develop, in Section 5.1, the rationale linking their bond portfolio re-balancing to changes in the term structure, in terms of fluctuations in the unobserved factors embedded in the observed term structure. We then, in Section 5.2, examine the possible importance of tail risk as a significant determinant of bond yields by estimating a structural vector auto regression model (SVAR) to test for the impact of tail risk on the estimated measures of the principal components constituting the term structure of the UK interest rates.

5.1 Short vs long maturities: Bond portfolio rebalancing

To model the impact of tail risk on the rebalancing of the UK pension funds' bond portfolios we develop the proposition below:

<u>Proposition</u>: Consider a portfolio consisting of two bonds, b_1 and b_2, and equity, E. The first bond is low risk, σ_{b1}, and low yield, r_{b1}, while the second bond is high risk, σ_{b2}, and high yield, r_{b2}; that is $r_{b1} < r_{b2}$ and $\sigma_{b1} < \sigma_{b2}$. The pension fund manager calculates the optimal total assets, TA, and the bond weight allocation vector W: (w_1, (1-w_1)) as a solution to the problem:

$$\max_{TA,W} TA\boldsymbol{r}'W, \text{ subject to } \alpha \mathrm{TA}\sqrt{W'\Omega W} \leq E$$

where $\Omega = \begin{bmatrix} \sigma_{b1}^2 & \sigma_{b1,b2} \\ \sigma_{b2,b1} & \sigma_{b2}^2 \end{bmatrix}$

With the Value-at-Risk at a certain confidence level (α) constraint characterising its 'risk tolerance', typically imposed by regulation, and E representing the value of the equity, it follows that $\frac{dw1}{dE} < 0$.

It is important to note that this is a prediction over and above the flight-to-safety. Indeed, here we are predicting that the pension fund suffering a shock to its equity value due to increased tail risk, will re-adjust its bond portfolio in favour of the 'safer' bond. Therefore, this proposition implies that when a pension fund is hit by a negative shock on its equity, that is *dE<0*, it will react by buying additional safer bonds (i.e., b_1), that is $dw_1>0$, whilst disposing of riskier bonds, (i.e., b_2), that is $d(1-w_1)<0$. By and large, long-term bonds are deemed riskier than the shorter maturity bonds. Thus, pension funds suffering, in terms of increasing tail risk and a reduction in the value of equity, will acquire more short-term bonds and sell or acquire less than usual long-term bonds. This will create unanticipated excess demand for shorter maturity bonds putting upward pressure on their prices. Therefore, the testable predictions are two-fold: i) tail risk impacts positively on the acquisition of shorter maturity and negatively on longer maturity bonds, and ii) tail risk reduces excess returns/yields for shorter maturity bonds.

We present a preliminary test for the first prediction using data obtained from the Office of National Statistics (ONS).[16] These data record the quarterly changes in the government bond holdings of independently administered pension funds from 1992 to 2017. The data are classified in terms of 'short-term' bonds whose maturity is less than 15 years (L15) and 'long-term' bonds with maturity equal to or greater than 15 years (M15), and it is given in terms of net investments (NI_XXX) and acquisitions (ACQ_XXX) in government bonds; where XXX is either L15 or M15. There are distinct differences in the statistical behaviour of these series. Whilst long-term bonds constitute the bulk of the bond portfolios of pension funds their trading is characterised by a great deal of persistence, measured by their autocorrelation, as they constitute strategic assets of the pension fund portfolios, whilst the trading of short-term bonds exhibits very limited memory characterising these assets as tactical responses to shocks in the overall value of the fund portfolio. Table 6 below shows the autocorrelation coefficients for all four categories.

Insert Table 6 about here

There are marked differences in persistence regarding the net investments in short- and long-term bonds, strongly indicating flow changes to the bond portfolios. Specifically, current trading of short-term bonds is loosely attached to its previous level, as it responds to immediate concerns of the fund manager. The observed high persistence of net investment of long-term bonds is indicative of their role as long-term acquisitions whose temporary price fluctuations are not fully compensated by altering their position in the pension fund portfolio. Overall, acquisitions for both types of bonds are reasonably stable indicating some inherent

[16] Our sample is sourced from the ONS publication '*MQ5: Investment by insurance companies, pension funds and trusts Statistical bulletins*', Office of National Statistics, accessed on 21 March 2019. (https://www.ons.gov.uk/economy/investmentspensionsandtrusts/bulletins/mq5investmentbyinsurancecompaniespensionfundsandtrusts/previousReleases)

fixed proportionality in the pension fund wealth portfolio. In comparisons to their long-term counterparts, short-term bond flows are more unpredictable, although such flows are a modest proportion of their total respective values in the fund portfolios.

We test the basic predictions of our proposition using the simple linear model below in terms of the net investments in these bonds:

$$(NI\_M15 - NI\_L15)_t = C_0 + C_1 TR_t + u_{NI,t}$$

in this model, the dependent variable is the difference between the net investment in long-term (NI_M15) and short-term bonds (NI_L15), expressed as a linear function of tail risk, TR, and $u_{NI,t}$ is an error term. We expect tail risk to have a negative impact on these portfolio adjustments. The monthly tail risk data has been converted into quarterly frequency to match the bond data. The estimated regression for the period January 1992 to December 2017 is presented in Table 7 below.

Insert Table 7 about here

The results provide encouraging preliminary evidence on the impact of equity tail risk on the changes in the bond portfolios of pension funds. The impact of tail risk on these portfolio adjustments is substantial as the resulting elasticity of the difference between net investments and tail risk exceeds 3. Specifically, increasing tail risk results in rapid rebalancing by the acquisition of additional short-term bonds in an effort to maintain the pre-set risk profile.

5.2 Impact of tail risk on term structure

In this section we investigate whether the re-balancing of pension funds' bond portfolios induced by tail risk has a statistically significant impact on the term structure of the UK interest rates. For that reason, we estimate a quarterly structural vector auto regression model of order 1 (SVAR(1)), over the period 1992q2 to 2017q4. Our model includes tail risk, net investment in short-term bonds, and the quarterly equivalent of the factors embedded in the term structure of interest rates. In the context of this model, we expect that shocks to tail risk will induce additional net investments in short-term bonds and these, and only these, will affect the term structure factors. Specifically, given the overall flight-to-safety phenomenon, we expect a negative change (temporary) of the level factor and a positive change in the curvature, as despite the fall in the level there is a relative stronger demand for short to medium maturity bonds compared to long maturity bonds. Regarding the slope factor, we also expect it to increase albeit from a lower position of the term structure.

In section 3, we report statistically significant factor loadings for tail risk in excess returns but not in yields. In comparison to excess bond returns and equity tail risk, bond yields are far less volatile. It is therefore less likely that such a dynamic factor will be associated with a significant factor loading when decomposing a comparatively yield curve. It may be the case that the impact of tail risk on the term structure is indirect, facilitated by another variable, that itself reacts to changes in tail risk and subsequently affects the yield curve via its impact on the constituent factors. The market conditions for bonds of different maturities are determined by the actions of agents involved in these markets. A major class of player in the government bond market are of course the pension funds. Their reactions to shocks in the equity market trigger portfolio readjustments in the bond market for selected maturities, and it is their action that result in excess demands in selected bond maturities, altering the shape and position of the yield curve.

We propose a simple model to test such sequence of impacts. That is tail risk alters investment decisions, namely the short bond net purchases of pension funds, and these are resulting in yield curve changes. Specifically, we estimate a structural SVAR(1) model of the form:

$$\boldsymbol{Y}_t = \boldsymbol{B}\boldsymbol{Y}_{\boldsymbol{t-1}} + \boldsymbol{u_t}$$

where $\mathbf{Y}_t$ is a vector that includes tail risk (TR), net investment in bonds with a maturity of less than 15 years, NI_L15, and the three principal components, PC, of the term structure (i.e., $\mathbf{Y}_t = \{TR_t, NI\_L15_t, d(PC1), PC2, PC3\}$), $\boldsymbol{u_t}$ is the matrix of structural residuals with zero mean and variance Σ (i.e., $\boldsymbol{u_t} \sim MN(\mathbf{0}, \boldsymbol{\Sigma})$), and $\boldsymbol{B}$ is a polynomial matrix in the lag operator.

We identify the system by imposing restrictions on both the ***B*** and ***Σ*** matrices to ensure that the only changes to the factors of the term structure are due exclusively to the bond portfolio rebalancing by pension funds. In terms of the mean equations there is no direct cascade of tail risk on the unobserved factors of the yield curve. Tail risk is simply used as a predictor on net bond purchases by pension funds. Subsequently these changes are predictors, without feedback, of the three principal components used in the yield curve decomposition. Thus, the mean equations for the system can be written are as follows:

$$\begin{bmatrix} TR \\ NI\_L15 \\ d(PC1) \\ PC2 \\ PC3 \end{bmatrix}_t = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 & 0 \\ 0 & b_{32} & b_{33} & b_{34} & b_{35} \\ 0 & b_{42} & b_{43} & b_{44} & b_{45} \\ 0 & b_{52} & b_{53} & b_{54} & b_{55} \end{bmatrix} \begin{bmatrix} TR \\ NI\_L15 \\ d(PC1) \\ PC2 \\ PC3 \end{bmatrix}_{t-1} + \begin{bmatrix} u_{TR} \\ u_{NI\_L15} \\ u_{d(PC1)} \\ u_{PC2} \\ u_{PC3} \end{bmatrix}_t$$

The shock transmission follows a very similar structure. The stochastic component of tail risk is taken as structural and it affects only the ransom element of the investment decisions, it does not cascade into the yield curve factors. In this manner we preserve the status of tail risk as an indirect factor of the yield curve. Subsequently, it is the structural errors of the investment decision equation that affect the principal components, again without feedback. We impose a reasonable hierarchy regarding the transmission of shocks across the level, slope and curvature. The relationship between the SVAR residuals, e, and the structural residuals, u, is given by:

$$e_{TR,t} = u_{TR,t}$$

$$e_{NIBL15,t} = c_{22}u_{TR,t} + u_{NI\_L15,t}$$

$$e_{d(PC1),t} = c_{32}u_{NI\_L15,t} + u_{d(PC1,t)}$$

$$e_{PC2,t} = c_{42}u_{NI\_L15,t} + c_{43}u_{d(PC1,t)} + u_{PC2,t}$$

$$e_{PC3,t} = c_{52}u_{NI\_L15,t} + c_{53}u_{d(PC1,t)} + c_{54}u_{PC2,t} + u_{PC3,t}$$

The model is estimated over the period 1992q2 to 2017q4, subject to the restrictions we impose, and its validity is tested against the fully unrestricted version of VAR.[17] The chi-squared likelihood ratio test, $\chi^2_{0.05,26}$, is 34.2 (critical value of 38.8), which provides strong support for the imposed restrictions. The model is well specified as the resulting Lagrange Multiplier (LM) statistics, presented in Table 8, for the SVAR residual independence do not reject the null hypothesis of no autocorrelation in the residuals of the SVAR model.

Insert Table 8 about here

Figure 6 shows the impulse response functions from the SVAR(1) model following a positive shock in tail risk. The estimated responses are statistically significant and indicate that such unanticipated developments in the equity market do trigger pension funds to seek safety by rebalancing their bond portfolios. Specifically, pension funds increase their net investment in short term bonds, as expected by theory, creating an overall excess demand for these bonds (i.e., the safe asset), raising bond prices and lowering yields overall, as the

[17] In the interest of brevity, we do not report the estimated SVAR coefficients but are available from the authors on request.

first factor falls, indicating a fall in the level of interest rates representing a downward shift of the curve. Apparently, there seems to be excess demand for bonds on the shorter/medium side of the maturity spectrum. After the tail risk shock, and as the net investment of pension funds increases and the yield curve shifts, the shorter-term yields are driven higher, compared to longer-term rates, increasing the slope as predicted. Furthermore, as pension fund managers do not substitute equity for money market instruments (i.e., very short-term bonds) but aim at replacing high yielding risky assets with safe assets that can still offer some yield, their excess demand for bonds is concentrated in the mid-maturity range resulting in raising the convexity of the term structure.

Insert Figure 6 about here

6. Conclusions

Using monthly data from January 1992 to December 2017 we report results that show strong impact of equity tail risk on the excess return of the UK government bonds. The Bank of England's monetary policy response over the last 10 years to sharp deteriorations in the equity market conditions, has been to aggressively lower interest rates. Investors' flight-to-safety during periods of market stress tends to exacerbate this trend. The combination of investors' behaviour and central bank's response results in strongly rising bond prices, for certain maturities, as the bond market rallies during difficult conditions in the equity market. In addition, we establish that tail risk emanated from the UK equity market is a significant predictor of the excess returns of government securities for medium maturities (i.e., 4-6 years) and for holding periods of one- and six-months. This association is robust independently of the numbers of risk factors used; three or five following ATSM in the predictive equations. We find that these relationships are robust as they maintain their statistical significance whilst augmenting both the predictive equations and decomposition factors by EPU that was shown to be an additional predictor of bond excess returns in the US bond market.

We further examine the impact of tail risk on the trading behaviour of independently administered UK pension funds and subsequently on the factors of UK's yield curve. Using quarterly data for the same period on the net investment of the pension funds in short- and long-term bonds, we find that tail risk does indeed impact trading behaviour and subsequently the factors underpinning the yield curve. A corollary to our investigation is that tail risk increases the net investment in relatively safer bonds (i.e., short-term), whilst decreasing the same measure of higher yielding and riskier long-term bonds.

All our empirical evidence indicates that the bond trading behaviour of the UK pension funds is consistent with flight-to-safety in the presence of increased equity tail risk. It appears that pension funds whilst investing strategically in long-term bonds they treat shorter-term government securities as tactical assets used partly to compensate for increased equity tail risk. The bond portfolio rebalancing executed by pension fund managers facing increasing equity tail risk, has a measurable and statistically significant effect on the UK term structure. This portfolio response, in the face of increased tail risk, shifts the curve temporarily downwards, whilst increasing both its slope and convexity, reflecting the hedging role of short-term bonds in the overall portfolios of pension funds whose assets are exposed to equity tail risk.

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Figure 1. FTSE All Share price index daily returns: January 1992 to December 2017
This figure shows the daily returns of the FTSE All Share price index from January 1992 to December 2017. All data comes from EIKON Refinitiv.

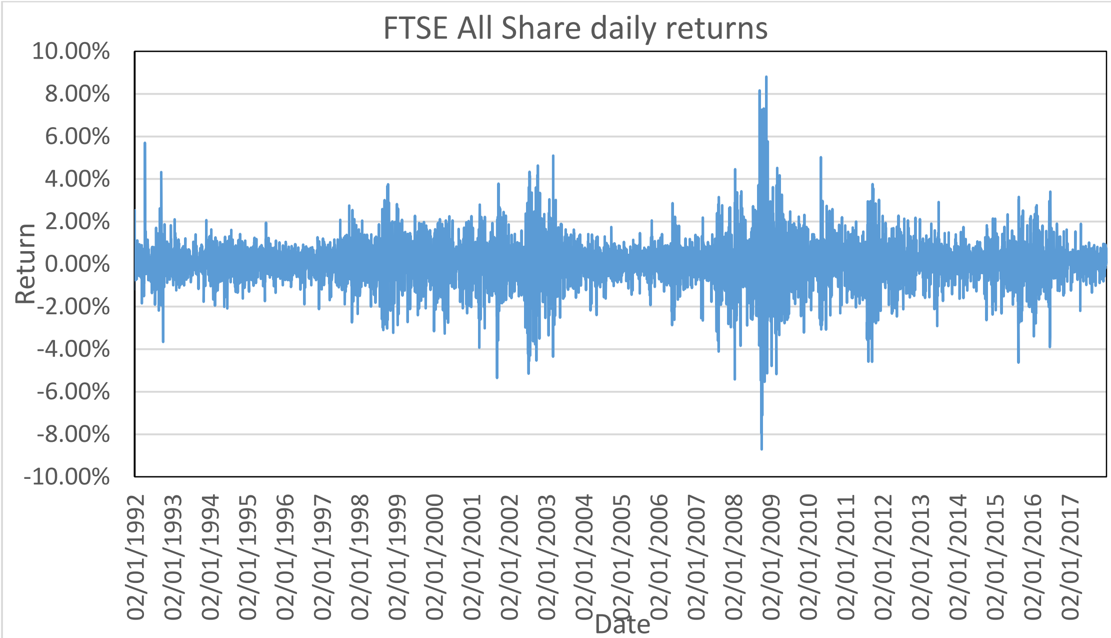

Figure 2. Economic Policy Uncertainty index: January 1992 to December 2017
This figure shows the Economic Policy Uncertainty index (EPU) developed by Baker et al. (2016), over the time period January 1992 to December 2017. The monthly data for the period January 1992 until January 1997 is annual data interpolated from historical EPU UK data. All data comes from https://www.policyuncertainty.com/.

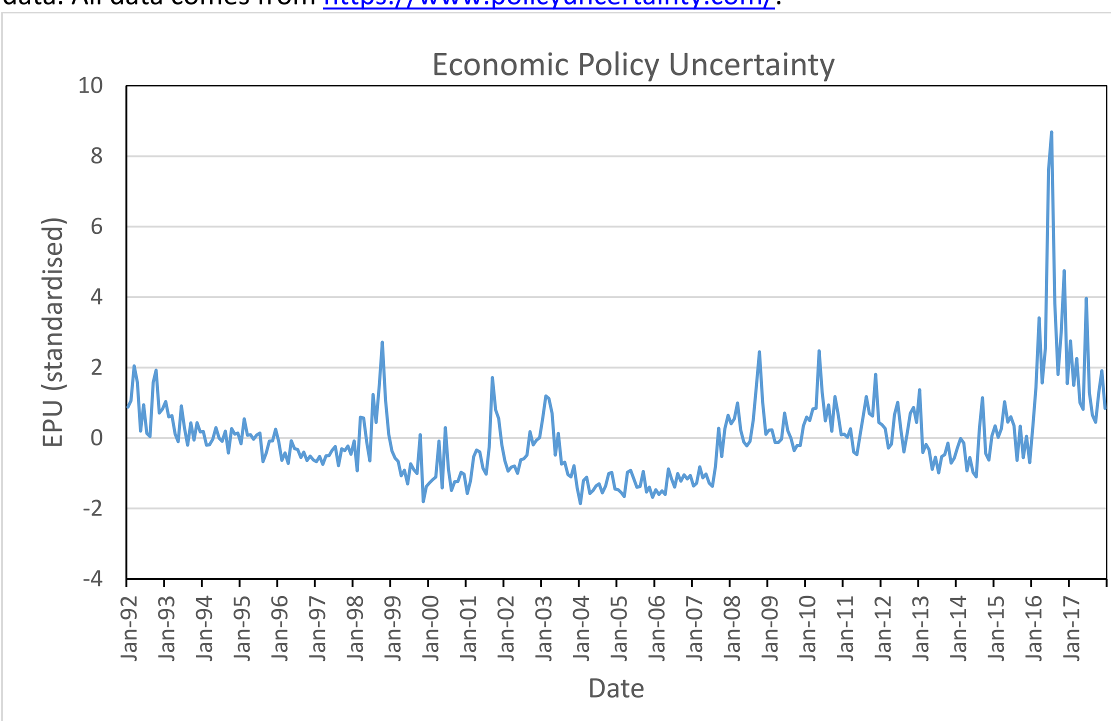

Figure 3. Aggregate equity tail risk: January 1992 to December 2017

This figure shows the aggregate equity tail risk in the UK stock market. Tail risk is estimated from the cross-section of daily returns of all FTSE All Share stocks, pooled over periods of one moth. The tail risk series have been scaled to have mean zero and variance of one. Tail risk is estimated using the returns of all FTSE All Share index constituent shares with data collected from EIKON Refinitiv.

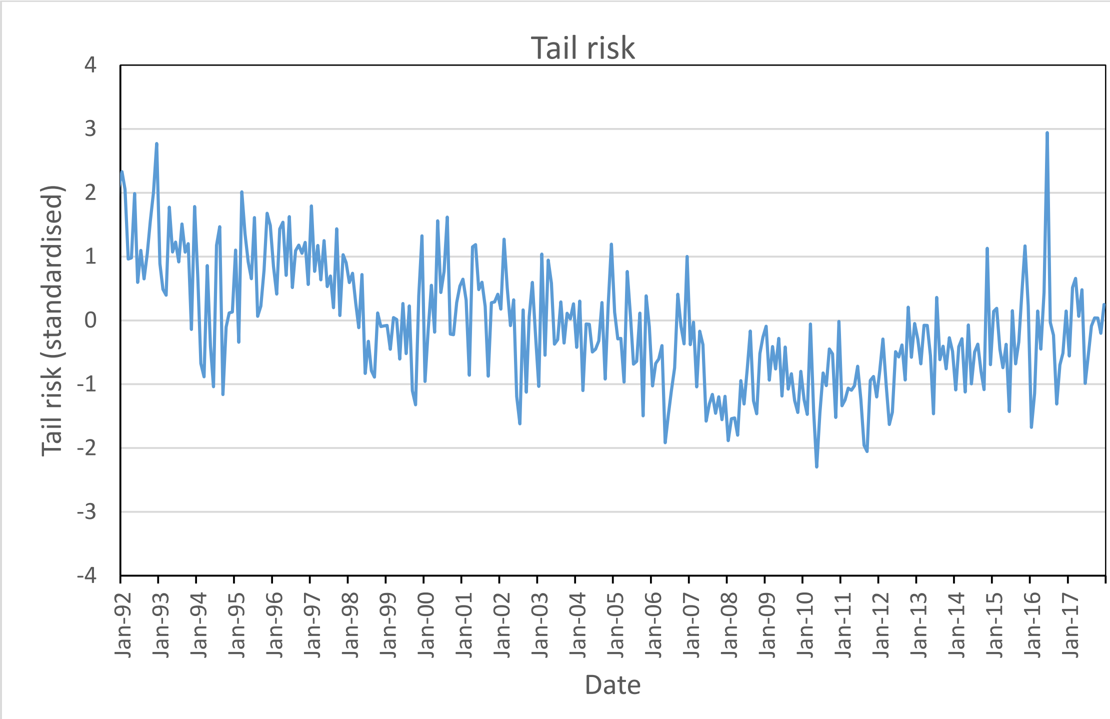

Figure 4. Factor combination 1: Factor loadings on excess returns

This figure shows the factor loadings for tail risk ('Tail') against maturity of the first five principal components, PC1, PC2, PC3, PC4, and PC5, of the term structure. The dashed lines show the 95% confidence intervals for the factor loadings computed following the procedure of Malik and Meldrum (2016) using 10,000 replications. The sample period is from January 1992 to December 2017. Tail risk is estimated using the returns of all FTSE All Share index constituent shares with data collected from EIKON Refinitiv, and bond data are obtained from the Bank of England.

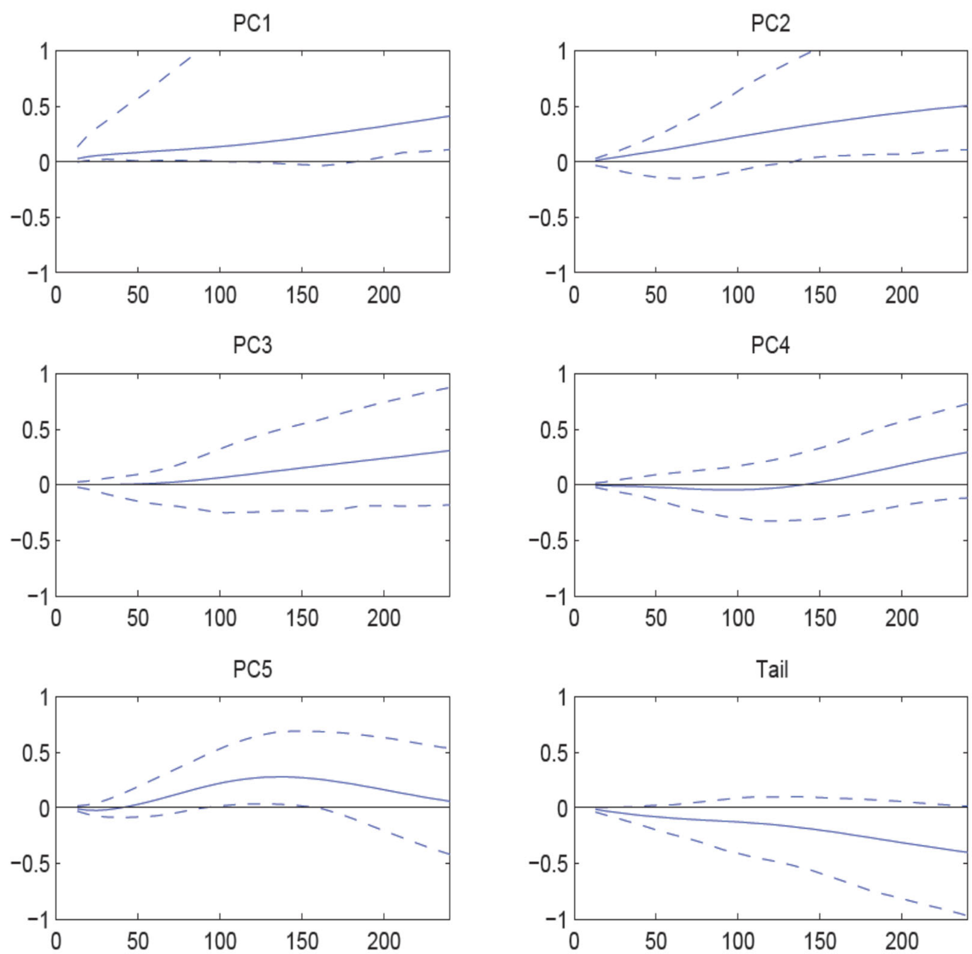

Figure 5. Factor combination 2: Factor loadings on excess returns

This figure shows the factor loadings for tail risk ('Tail') and Economic Policy Uncertainty ('EPU') against maturity of the first three principal components, PC1, PC2, and PC3, of the term structure. The dashed lines show the 95% confidence intervals for the factor loadings computed following the procedure of Malik and Meldrum (2016) using 10,000 replications. The sample period is from January 1992 to December 2017. Tail risk is estimated using the returns of all FTSE All Share index constituent shares with data collected from EIKON Refinitiv. Bond data are obtained from the Bank of England and the EPU data are obtained from https://www.policyuncertainty.com/.

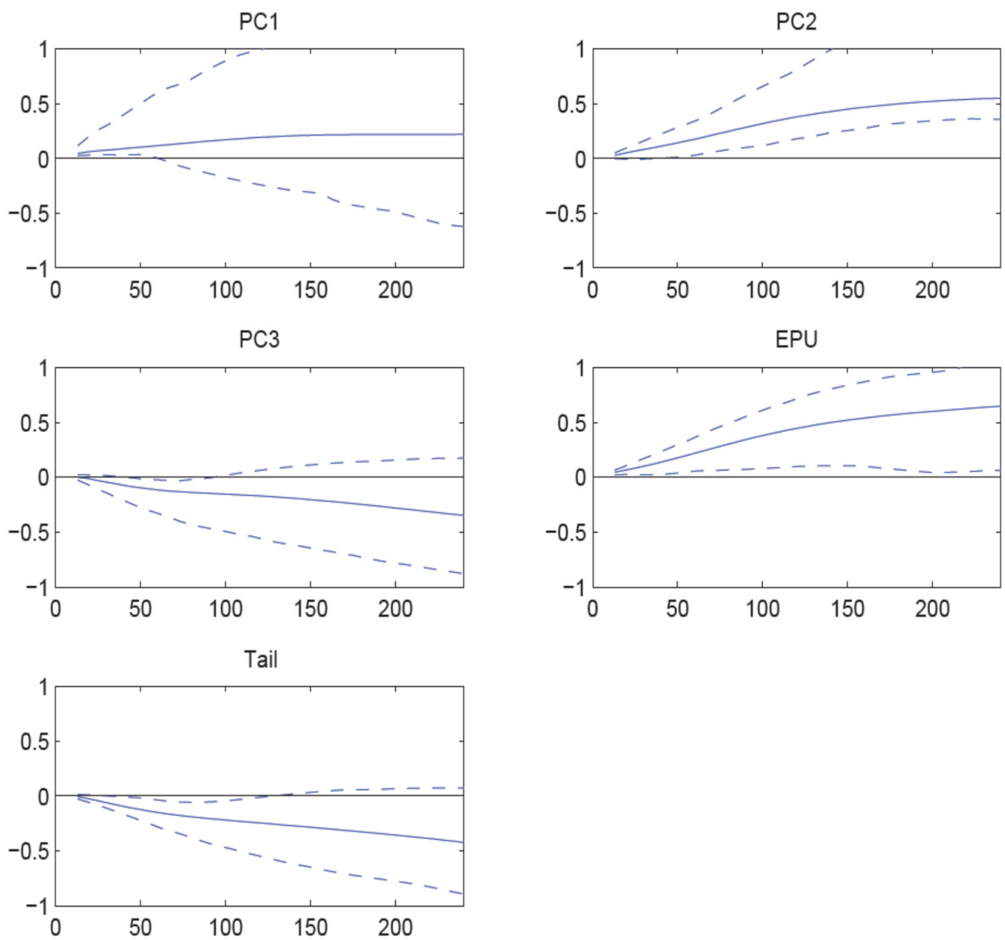

Figure 6. Impulse response functions

This figure shows the impulse response functions from a SVAR(1) model following a shock in tail risk ('Tail') of plus or minus one standard deviation from its long run average. The dashed lines show the 95% confidence intervals for the calculated impulse response functions. Tail risk is estimated using the returns of all FTSE All Share index constituent shares with data collected from EIKON Refinitiv, and bond data are obtained from the Bank of England. The sample period is from January 1992 to December 2017.

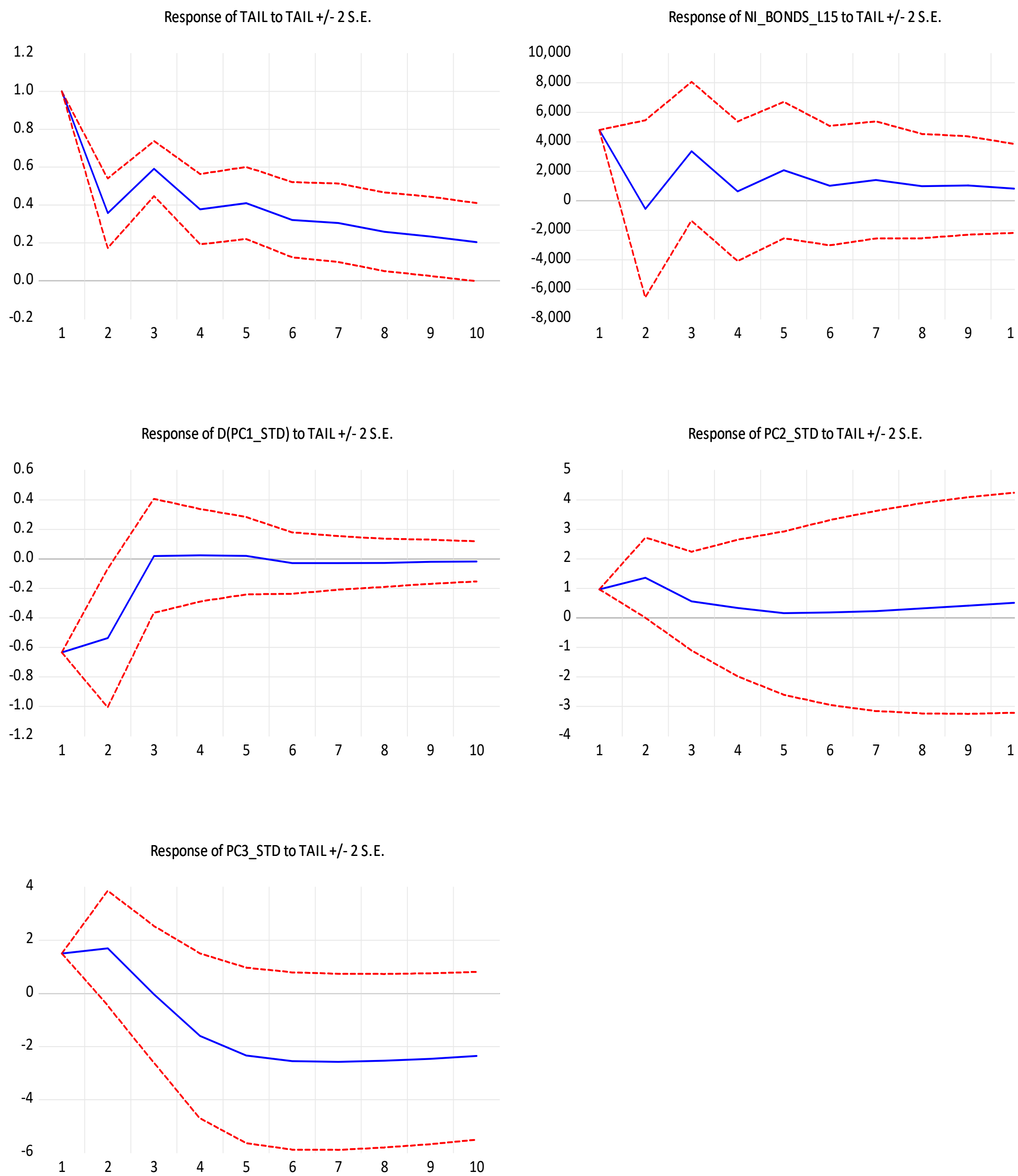

Table 1. Net investment and acquisitions of government bonds by UK pension funds

This table contains summary statistics for the UK self-administered pension funds in terms of net investments ('Net Investments') and acquisitions ('Bond Acquisitions') of government bonds, over the period from January 1992 to December 2017. Data are grouped into short and medium maturity bonds ('Short/medium maturity') and long maturity bonds ('Long maturity'), with the first group containing figures for government bonds with maturity of less than 15 years, and the second group containing figures for government bonds with maturity equal or greater than 15 years. 'Mean' and 'St.Dev' denote the average value and the standard deviation of net investments and acquisitions of the UK pension funds in government bonds, respectively. 'Min' and 'Max' denote the minimum and maximum values of net investments and acquisitions, respectively, and 'J-B (*p*-value)' denotes the *p*-value of the Jarque-Bera statistic that tests the hypothesis that the data are generated from a normal distribution. ONS defines net investments to be the difference between levels of acquisitions and disposals of assets by pension funds, and acquisitions as the procurement of assets (i.e., gilts and shares). All data are reported in current prices in millions of GBP (£) and come from the Office of National Statistics (ONS).

Panel A: Net Investments (in millions £)

	Short/medium maturity (< 15 years)	**Long maturity (>15 years)**
Mean	-135	5,141
St.Dev	1,300	3,394
Min	-4,826	-463
Max	2,711	15,675
J-B (*p*-value)	0.000	0.016
Total	-14,033	53,4616

Panel B: Bond Acquisitions (in millions £)

	Short/medium maturity (< 15 years)	**Long maturity (>15 years)**
Mean	7,845	7,173
St.Dev	3,118	5,239
Min	1,784	456
Max	16,257	26,970
J-B (*p*-value)	0.331	0.000
Total	815,858	746,012

Table 2. Correlation Coefficients between the observed and expected excess returns for selected maturities

This table reports the estimated correlation coefficients between the observed and the estimated expected returns for 24-months, 60-months, 120-months, and 240-months maturity bonds. The expected returns are estimated using the five principal components ($5PC$) model with and without tail risk ($Tail$). Bond data are obtained from the Bank of England. The sample period is from January 1992 to December 2017.

Maturity/Factor combinations	24-month	60-month	120-month	240-month
$5PC$	0.130	0.123	0.184	0.162
$5PC + Tail$	0.151	0.154	0.182	0.127

Table 3. Estimated coefficients of tail risk for a holding period of one month

This table reports the estimated coefficients of tail risk ($\gamma', \gamma'', \gamma'''$) of the three regression models below (M1, M2, and M3) used to test the predictive contribution of tail risk to the excess returns of UK government bonds whose maturities range from 1 to 20 years, for a holding period of one month.

Model 1 (M1): $xr_{i,t} = \sum_{j=1}^{3} \beta_i PC_{j,t} + \gamma_i^{'} Tail_t + u_{M1,t}$

Model 2 (M2) $xr_{i,t} = \sum_{j=1}^{5} \beta_i^{*} PC_{j,t} + \gamma_i^{''} Tail_t + u_{M2,t}$

Model 3 (M3) : $xr_{i,t} = \sum_{j=1}^{3} \beta_i^{+} PC_{j,t} + \gamma_i^{'''} Tail_t + \delta_i EPU_t + u_{M3,t}$

where $i = 1, \cdots, 20$ years denotes maturity, xr denotes the bond excess returns, '$Tail$' denotes tail risk, 'PC' denotes the unobserved factors extracted from the decomposition of the cross-sectional structure of the term structure of the UK interest rates, and $u_{M,t}$ denoted the stochastic component of excess returns. Conventionally, the three basic factors are the level, slope, and curvature (i.e., convexity), which we also augment by two additional factors following the methodology of ASTM. In all predictive regressions a holding period of six months is used. The first model (M1) includes the three principal components ($3PC$) and tail risk ($Tail$) as predictors, the second model (M2) includes the five principal components ($5PC$) and tail risk ($Tail$) as predictors, and the third model (M3) includes the three principal components ($3PC$), tail risk ($Tail$), and the Economic Policy Uncertainty (EPU) as predictors. *p*-values with bootstrapped standard errors are given in parentheses. Tail risk is estimated using the returns of all FTSE All Share index constituent shares with data collected from EIKON Refinitiv. Bond data are obtained from the Bank of England and the EPU data are obtained from https://www.policyuncertainty.com/.

Model/Maturity	1-year	2-years	3-years	5-years	7-years	10-years	15-years	20-years
M1:	-0.016	-0.044	-0.079	-0.156	-0.232	-0.322	-0.400	-0.435
($3PC + Tail$)	(0.18)	(0.12)	(0.07)	(0.04)	(0.03)	(0.04)	(0.06)	(0.10)
M2:	-0.022	-0.052	-0.081	-0.126	-0.126	-0.218	-0.357	-0.499
($5PC + Tail$)	(0.12)	(0.09)	(0.09)	(0.12)	(0.16)	(0.19)	(0.12)	(0.09)
M3:	-0.22	-.073	-0.126	-0.202	-0.249	-0.291	-0.337	-0.399
($3PC + Tail + EPU$)	(0.11)	(0.02)	(0.04)	(0.02)	(0.04)	(0.10)	(0.17)	(0.20)

Table 4. Estimated coefficients of tail risk for a holding period of six months

This table reports the estimated coefficients of tail risk (TR) ($\gamma', \gamma'', \gamma'''$) of the three regression models below (M1, M2, and M3) used to test the predictive contribution of tail risk to the excess returns of UK government bonds whose maturities range from 1 to 20 years, for a holding period of six months.

Model 1 (M1): $xr_{i,t} = \sum_{j=1}^{3} \beta_i PC_{j,t} + \gamma_i^{'} Tail_t + u_{M1,t}$

Model 2 (M2) $xr_{i,t} = \sum_{j=1}^{5} \beta_i^{*} PC_{j,t} + \gamma_i^{''} Tail_t + u_{M2,t}$

Model 3 (M3) : $xr_{i,t} = \sum_{j=1}^{3} \beta_i^{+} PC_{j,t} + \gamma_i^{'''} Tail_t + \delta_i EPU_t + u_{M3,t}$

where $i = 1, \cdots, 20$ years denotes maturity, xr denotes the bond excess returns, '$Tail$' denotes tail risk, 'PC' denotes the unobserved factors extracted from the decomposition of the cross-sectional structure of the term structure of the UK interest rates, and $u_{M,t}$ denoted the stochastic component of excess returns. Conventionally, the three basic factors are the level, slope, and curvature (i.e., convexity), which we also augment by two additional factors following the methodology of ASTM. In all predictive regressions a holding period of six months is used. The first model (M1) includes the three principal components ($3PC$) and tail risk ($Tail$) as predictors, the second model (M2) includes the five principal components ($5PC$) and tail risk ($Tail$) as predictors, and the third model (M3) includes the three principal components ($3PC$), tail risk ($Tail$), and the Economic Policy Uncertainty (EPU) as predictors. *p*-values with bootstrapped standard errors are given in parentheses. Tail risk is estimated using the returns of all FTSE All Share index constituent shares with data collected from EIKON Refinitiv. Bond data are obtained from the Bank of England and the EPU data are obtained from https://www.policyuncertainty.com/.

Model/Maturity	**1-year**	**2-years**	**3-years**	**5-years**	**7-years**	**10-years**	**15-years**	**20-years**
M1:	-0.034	-0.146	-0.289	-0.559	-0.758	-0.873	-0.721	-0.312
($3PC + Tail$)	(0.119)	(0.038)	(0.013)	(0.005)	(0.005)	(0.019)	(0.147)	(0.529)
M2:	-0.018	-0.174	-0.313	-0.520	-0.627	-0.664	-0.699	-0.764
($5PC + Tail$)	(0.350)	(0.022)	(0.013)	(0.014)	(0.029)	(0.019)	(0.182)	(0.241)
M3:	-0.055	-0.199	-0.137	-0.571	-0.685	-0.645	-0.190	0.456
($3PC + Tail + EPU$)	(0.042)	(0.013)	(0.004)	(0.005)	(0.012)	(0.085)	(0.699)	(0.451)

Table 5. Out-of-sample forecasting contribution of tail risk

This table reports the mean-squared error ratios MSE (=MSE^{AFM}/MSE^{BM}), of the out-of-sample comparison of the monthly excess bond returns. MSE^{AFM} denotes the mean-squared forecasting error of the model that includes the additional forecasting factors of tail risk ($Tail$) and Economic Policy Uncertainty (EPU), and MSE^{BM} denotes the mean-squared forecasting error of the benchmark models that include only either the three ($3PC$) or five principal components ($5PC$) of the term structure. We conduct the analysis and report the results for two different learning in-sample time periods. The first one, October 1992 to December 2007, excludes the financial crisis, while the second one, October 1992 to December 2012, includes the financial crisis and ends at the beginning of the recovery. The *p*-values of the Clark and West (2007) mean-squared forecasting error adjusted test for equal forecasting accuracy are given in parentheses. Tail risk is estimated using the returns of all FTSE All Share index constituent shares with data collected from EIKON Refinitiv. Bond data are obtained from the Bank of England and the EPU data are obtained from https://www.policyuncertainty.com/.

Panel A: October 1992 to December 2007

	MSE^{AFM}/MSE^{BM}							
Comparison models	**1-year**	**2-years**	**3-years**	**5-years**	**7-years**	**10-years**	**15-years**	**20-years**
$3PC + Tail\ vs.\ 3PC$	0.997	0.992	0.989	0.989	0.994	1.002	1.011	1.016
(*p*-value)	(0.126)	(0.104)	(0.096)	(0.103)	(0.131)	(0.195)	(0.320)	(0.417)
$5PC + Tail\ vs.\ 5PC$	0.989	0.984	0.986	0.993	1.000	1.004	1.005	1.004
(*p*-value)	(0.052)	(0.024)	(0.045)	(0.100)	(0.279)	(0.378)	(0.348)	(0.292)
$3PC + Tail + EPU\ vs.\ 5PC$	0.918	0.879	0.853	0.857	0.886	0.918	0.948	0.985
(*p*-value)	(0.012)	(0.004)	(0.004)	(0.006)	(0.010)	(0.017)	(0.018)	(0.022)

Panel B: October 1992 to December 2012

	MSE^{AFM}/MSE^{BM}							
Comparison models	**1-year**	**2-years**	**3-years**	**5-years**	**7-years**	**10-years**	**15-years**	**20-years**
$3PC + Tail\ vs.\ 3PC$	1.023	0.993	0.996	1.015	1.032	1.051	1.068	1.076
(*p*-value)	(0.257)	(0.174)	(0.196)	(0.304)	(0.425)	(0.576)	(0.727)	(0.810)
$5PC + Tail\ vs.\ 5PC$	1.015	0.979	0.991	1.012	1.025	1.037	1.053	1.064
(*p*-value)	(0.174)	(0.091)	(0.074)	(0.405)	(0.587)	(0.725)	(0.788)	(0.811)
$3PC + Tail + EPU\ vs.\ 5PC$	1.707	1.211	1.067	0.989	0.972	0.977	1.002	1.029
(*p*-value)	(0.077)	(0.064)	(0.025)	(0.015)	(0.020)	(0.041)	(0.126)	(0.246)

Table 6. Autocorrelation coefficients for pension funds government bond positions

This table shows the autocorrelation coefficients for up to four lags of the UK pension funds' net investments and acquisitions in government bonds. '*NI_L15*' and '*NI_M15*' denote net investment in short- and long-term bonds, respectively, while '*ACQ_L15*' and '*ACQ_M15*' denote acquisitions in short- and long-term bonds, respectively. As short-terms bonds are defined the bonds with maturity of less than 15 years, and as long-term bonds are defined the bonds with a maturity equal to or greater than 15 years. All data are quarterly and come from the Office of National Statistics (ONS). The sample period is from January 1992 to December 2017.

Number of lags	*NI_L15*	*NI_M15*	*ACQ_L15*	*ACQ_M15*
1	0.278	0.801	0.819	0.890
2	0.335	0.766	0.754	0.783
3	0.258	0.670	0.740	0.682
4	0.251	0.602	0.683	0.651

Table 7. Impact of tail risk on pension fund bond portfolios

The table contains the estimated coefficients C_0 and C_1 of the regression model we use to examine the relation between the difference between the net investment in long-term (*NI_M15*) and short-term bonds (*NI_L15*) and tail risk ($Tail$). $u_{NI,t}$ is the error term. The *t*-statistics are given in parentheses. The pension fund bond portfolio quarterly data come from the Office of National Statistics (ONS) and tail risk is estimated from data collected from EIKON Refinitiv. The sample period is from 1992q1 to 2017q4.

$$(NI\_M15 - NI\_L15)_t = C_0 + C_1 Tail_t + u_{NI,t}$$

C_0	C_1
20346.94	-37,166.82
(8.666)	(-6.678)
Number of observations: 103	Adjusted-R^2 = 0.27

Table 8. Lagrange Multiplier autocorrelation test for SVAR(1)

This table reports the Lagrange Multiplier (LM) statistics for the SVAR model residual independence (i.e., no autocorrelation) for up to four lags. The LM statistic follows a chi-squared distribution with $n-1$ degrees of freedom, where n is the number of the estimated parameters. The sample period is from 1992q1 to 2017q4.

Number of lags	*p*-value
1	0.122
2	0.950
3	0.659
4	0.587