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Asymmetric expectations of monetary policy

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Filippo Busetto

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Abstract

We study the determinants of the asymmetric behaviour of monetary policy expectations in the United States, Germany and the United Kingdom. A common factor based on macroeconomic data and survey variables has predictive ability above and beyond yield based factors for negative changes in expected rates during an easing cycle, but not for increases in expected rates during a tightening in monetary policy. At the same time, macroeconomic information does not have any asymmetric effect on the conditional distribution of term premia. We complement previous findings on the asymmetric predictability of expected rates by showing that monetary policy easing during crises is predictable. This is also relevant for policymakers, as the yield curve does not always provide an accurate picture of the expected future stance of monetary policy at turning points.

Key words: Interest rates, monetary policy, macro-finance, quantile regressions.

JEL classification: E43, E44, E52, E58.

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(1) Bank of England. Email: filippo.busetto@bankofengland.co.uk

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Bank of England, Threadneedle Street, London, EC2R 8AH
Email: enquiries@bankofengland.co.uk

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1 Introduction

Monetary policy expectations extracted from the yield curve vary substantially over the business cycle, and their changes are typically asymmetric. At the start of a tightening cycle, markets usually price a less aggressive path for monetary policy than what is actually observed, while incorrectly pricing a quick reversal later in the cycle. During a monetary easing cycle, expectations for the policy rate adjust downwards relatively fast, but then incorrectly price a rise in the policy rate much earlier than the realised future path of policy (Figure 1 shows this pattern for the Bank Rate in the UK). As the market-implied path of expected rates is a measure of the expected stance of monetary policy, it is carefully analysed from central bank policymakers. If factors extracted from the contemporaneous yield curve cannot explain all of this time-series and cross-sectional variation, then other information not contained in the term-structure of interest rates must be able to account for some of this behaviour.

In this paper, we focus on whether the transmission of macroeconomic information to the term-structure of interest rates changes across different monetary policy cycles in the United States, United Kingdom and Germany. In other words, is the information provided by macroeconomic variables not included in the factors extracted from interest rates at certain times? Specifically, we focus on the conditional distribution of observed yields, expected short-term interest rates and term premia obtained semi-parametrically thanks to quantile regressions. We decompose yields using an Affine Dynamic Term Structure model (ATSM), as this enhances our understanding of the drivers behind this asymmetric behaviour. We check whether common or domestic macroeconomic factors extracted from a large set of macroeconomic and survey variables can predict the conditional quantiles of observed interest rates and of these two interest rate components above and beyond yield-based factors.

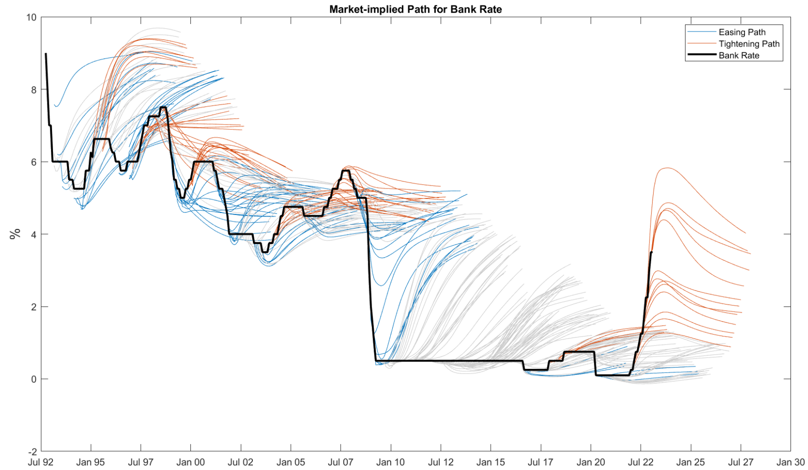

Figure 1: Market-implied path for Bank Rate
The black line represents the path for Bank Rate in the UK between January 1992 and December 2022. The blue, orange and grey lines show the market-implied path for Bank Rate extracted from OIS rates during easing cycles, tightening cycles and at peaks or through, respectively.

Indeed, the lower quantiles of the distribution of the future change in yields vary over time as a function of a common macroeconomic factor, and this effect is driven by expected rates. Thus, our Common Factor (henceforth CF) has an asymmetric effect on the expectations of short-term interest rates, as it shows predictive power for significant negative changes in future expected rates caused by a sizable easing in monetary policy. This result is economically significant, as a change by one standard deviation in the CF causes a decrease in 5-year average future expected rates of 28, 20 and 40 basis points in the United States, Germany and the United Kingdom, respectively, at the three-month horizon.

However, these magnitudes greatly decrease when focusing on the right tail of the empirical distribution. Consequently, the upper quantiles of the conditional distribution are more stable and driven by yield-based factors. In this case, the CF has no predictive information for the upper quantiles of future changes in expected rates – a strong tightening in monetary policy. This result would appear to be at odds with previous research that points to the unpredictability of rate cuts compared to rate hikes. Cieslak (2018) and Schmeling et al. (2022) show that information extracted from Fed Funds Futures and surveys on expected rates helps to predict tightening cycles, but not big rate cuts. In similar vein, Bauer et al. (2022) show how the how investors' perception of the central bank reaction function changes over the business cycle, with the perceived monetary policy rule being stronger during tightening cycles as the central bank appears to be more data driven. Our results are not inconsistent with this view. Our analysis shows that the amount of macroeconomic information contained in the yield curve changes over monetary policy cycles. This is consistent with time-varying reactions of the yield curve to macroeconomic news. If the yield curve reacts less at certain times to macroeconomic releases, it is more likely that not all of the relevant macroeconomic information useful to forecast interest rates is embedded in market prices straight away. Further, our result is also consistent with the previous findings by Greenwood et al. (2022) and Schularick and Taylor (2012), which point out that financial crises are predictable. If that is indeed the case, we should also be able to predict the accomodative monetary policy response to such crises. Our results hold out-of-sample, as adding the CF on top of the level, slope and curvature factors extracted from the yield curve improves the quantile pseudo-R^2 by 23.5 percentage points for the United States, 17.1pp for Germany and 38.9pp for the United Kingdom when focusing on the left tail of the distribution. We do not observe these big out-of-sample forecasting gains when looking at either the median or the right tail of the empirical distribution. While we also do find that yield-based factors have some asymmetric effect on future expected rates, the information provided by our CF goes above and beyond the one contained in the term structure of interest rates.

Further, the effect of either the CF or country-specific local factors (LFs) are not asymmetric on the term premia component. In fact, while in some cases these two factors improve the conditional forecast, the observed quantile coefficients do not change significantly at different points of the conditional distribution. However, as most of the significance of the LF coefficients related to changes in term premia are still found on the tails of this variable, it raises the possibility that most of the results in the literature that point to the presence of unspanned factors in the yield curve might be driven by a few data points, namely big swings in each direction of term premia.

We also transform the empirical quantile distribution into an estimated conditional density of expected short rates thanks to the non-parametric approach of Mitchell et al. (2022). When we add the CF as a conditioning variable, the predicted densities shift to the left and show negative skewness during crisis periods, while this effect is not captured when we employ solely yield-based factors. At the same time, adding the CF does not change the shape of the right tail of the distribution. This asymmetry in the evolution of future expected short-term rates demonstrates the much stronger time variation of downside risk for this variable compared with upside risk.

We contribute to the literature in three main ways. First, our work justifies the macro-financial view of the yield curve. Our analysis points to the presence of unspanned risks, which are not captured by factors extracted from the contemporaneous yield curve. This strand of research usually employs predictive regressions for bond excess returns – a measure related to our term-premia component – on several predictors, controlling for principal components extracted in the contemporaneous yield curve. For example, Greenwood and Vayanos (2014) find that bond supply is unspanned by yield-based factors. Other papers such as Cochrane and Piazzesi (2005), Joslin et al. (2014), Haddad and Sraer (2020), Gargano et al. (2019), Cieslak and Povala (2015) and Ludvigson and Ng (2009) show similar findings for other variables such as a combination of forward rates, GDP, inflation, inflation expectations, banks' balance sheet exposure to interest rates and factors extracted from large sets of macroeconomic variables. Bauer and Chernov (2021) show that yield skewness can predict shifts in the perception of interest rate risks and anticipate turning points in monetary policy. All of these variables appear to provide additional predictive information on bond returns, thus advocating for the use of unspanned term-structure models in which these additional factors are not a linear combination of yield-based principal components. At the same time, other research (Bauer and Rudebusch (2016), Bauer and Hamilton (2017)) demonstrates the severe bias in these regressions due to both overlapping returns and the underlying trend in some of these unspanned factors. Accordingly, this leads to a biased inference of the predictive power of these factors on bond returns, which greatly diminishes when accounting for these drawbacks. Another strand of related research focuses on the predictability of monetary policy shocks extracted from high-frequency interest rate surprises around central bank announcements. Miranda-Agrippino (2016), Miranda-Agrippino and Ricco (2021), Bauer and Swanson (2023) and Cieslak (2018) show that these shocks are correlated with macroeconomic news released prior to monetary policy decisions. While we do perform predictive regressions, we focus instead on the predicted empirical quantiles and conditional density of expected short-term rates and term premia at several horizons, which presents a more complete picture of the effects of macro factors on these interest rate components.

Second, our paper is also connected to studies on international bond risk premia. Zhu (2015), Dahlquist and Hasseltoft (2016) and Abbritti et al. (2018) show how global factors can predict international bond returns, while Zhao et al. (2021) observe the unspanned properties of these global factors on local and global yield curves. Fujiwara et al. (2013) find that developed countries bond excess returns are asymmetric and that past returns and liquidity are a driving factor of this asymmetry. While we estimate a common macroeconomic factor that affects yield curves in multiple countries, we are interested in modelling the entire conditional distribution of interest rates. The other existing research in this literature focuses instead on point forecasts, thus missing the potential variation caused by macroeconomic dynamics at other points of the conditional distribution.

Finally, this paper is linked to studies applying quantile regression techniques to both financial and macroeconomic variables. Among others, Adrian et al. (2019), Giglio et al. (2016), Lloyd et al. (2021), and Lopez-Salido and Loria (2022) and Aikman et al. (2019) study macroeconomic tail risks. Strictly related to us, Cenedese et al. (2014), Eguren-Martin and Sokol (2022) and Ostry (2023) focus on the conditional distribution of exchange rates, while Crump et al. (2018) applies similar techniques to the equity market. To the best of our knowledge, we are the first to build an empirical density for expected short-term interest rates and term premia conditional on yield-based and macroeconomic factors.

The remainder of the paper is structured as follows: Section 2 shows how we decompose interest rates into expected short-rates and premia. Section 3 describes how we build our common and local country-specific economic factors. Section 4 explains the quantile regression setup. Section 5 shows our empirical results. In section 6 we perform several robustness tests to our findings. Section 7 concludes.

2 Decomposing Interest Rates

We decompose interest rates using an affine dynamic term structure model (ATSM). The components of a no-arbitrage term-structure model are the following: a time-series model for the risk factors, a dynamic specification for the factors under a risk-neutral measure and an equation relating short-term interest rates to the risk factors. Short-term interest rates are affine in the risk factors:

$$i_t = \delta_0 + \delta_1 P_t. \tag{1}$$

The risk factors follow a VAR (1) under both the physical and the risk-neutral measure:

$$P_t = K_0^{\omega} + K_1^{\omega} P_{t-1} + \Sigma\epsilon_t^{\omega}, \quad \epsilon_t \sim N(0, I_n). \tag{2}$$

with $\omega = P, Q$ for the physical and risk-neutral distribution, respectively. Under these assumptions, bond yields are affine in the pricing factors:

$$Y_n = A_n + B_n P_n. \tag{3}$$

The parameter set for the loadings A and B is then $\Theta = (K_0^Q, K_1^Q, \delta_0, \delta_1, \Sigma)$. A and B can then be estimated recursively as:

$$A_{n+1} = A_n + B_n^{\text{`}} K_0^Q - \frac{1}{2} B_n^{\text{`}} \Sigma B_n + \delta_0 \tag{4}$$

$$B_{n+1}^{\text{`}} = \delta_1^{'} + B_n^{'} K_1^Q. \tag{5}$$

Identification in this kind of models can be achieved by imposing some restrictions on the parameters set. We follow the identification proposed by (Joslin et al., 2011)(commonly known as the JSZ model). The JSZ specification is one of the main work-horse affine models in the term-structure literature, and it is widely used by central banks and practitioners. Yields can also be decomposed into an ”expectation component” (E), which is the hypothetical yield that would be observed under the expectation hypothesis, and a ”term premia” (TP), such as

$$y_t^n = \underbrace{\frac{1}{n} E_t^P \sum_{k=0}^{n-1} i_t}_{E_t^n} + TP_t^n. \tag{6}$$

While for yields themselves it is only the risk-neutral parameters of the model that enter A and B, we can recover the expectations component from the physical parameters estimated from the model, while the term premium is a function of both sets of parameters.

$$E_t^n = A_n^{EC} + B_n^{EC'} P_t \tag{7}$$

$$TP_t^n = A_n^{TP} + B_n^{TP'} P_t \tag{8}$$

Our pricing factors are yield-based, namely principal components (PCs) extracted from the cross-section of bond yields. We show the first three principal components extracted from yields in Figure 2. These are commonly known in the literature as level, slope and curvature factors. We use the first $N = 4$ principal components extracted from interest rates in our estimation. We download end-of-month yields from Bloomberg with maturities of 3 months and 1 to 10 year and estimate the model for each country separately. We show in Figure 3 10-year yields for the US, DE and UK and full-sample estimates for the expectations and term premia components.

However, the variables we use in our paper are obtained recursively. As our focus is on forecasting the two yield components explained above (E and TP), estimating the model on the full sample would introduce look-ahead bias in the estimates of E and TP. As full-sample parameters might be quantitatively different from real-time ones, updating parameters can be an important source of variation in risk premiums, as also pointed out by Giacoletti et al. (2021). Thus, we estimate the model for the first 10 years of data and then update the parameters each month of the remaining sample. This makes sure that all changes in our components are in real-time. Our sample period covers the period between 1980-01 and 2019-12. We initially estimate the term-structure model until 1990-01 and then update the model parameters each month until the last data point.

As previously stated, our main variables of interest are changes in expectations and term premia at different horizons:

$$\Delta y^{\tau}_{t,t+h} = y^{\tau}_{t+h} - y^{\tau}_{t} \quad y = E, TP \tag{9}$$

where y^{τ} is either the expectation or term premia component for the yield with τ maturity estimated from our term-structure model. We focus on quarterly, half-yearly and yearly changes. As the cross-sectional correlation of these changes is very high, we average these changes across some maturities:

$$\overline{y}_{t+h} = \frac{1}{n} \sum_{\tau=1}^{5} y^{\tau}_{t+h} - y^{\tau}_{t}. \tag{10}$$

In Figure 4 and 5 we show the 3 and 12-month changes for these variables (expectations in the upper panel, term premia in the lower panel). As expected, the expectation component is cyclical, as the monetary policy stance eases during recessions, thus compressing the expectation component of interest rates. This is clearly visible at both horizons. Interpreting term premia is more complicated, as changes in this component can be caused by several factors. For example, when risk aversion is high, risk-free assets of highly rated government bonds can experience flight-to-safety episodes (Baele et al. (2020)), thus causing a compression in term premia. At the same time, during other episodes of market dysfunction, such as the onset of the Covid-19 Pandemic, a dash-for-cash episode caused a spike in US Treasuries and other advanced economies bond risk premia (Vissing-Jorgensen (2021), Corradin et al. (2021)). Among the three countries in our study, it appears the US experiences a reduction in TP during crises, while the UK experiences the opposite effect. Germany is a in-between these two countries, as it displays more stability in TP during crises after the early 2000s as the Bund became the safe-haven asset for the euro area. Our term premia estimates seem to be consistent with the US Treasury market being considered the main ”safe haven” during recessionary periods, while the other two countries are less-likely to experience the same increase in demand at similar times.

3 Extracting Macro Factors

In order to compute a common macro factor to use into our regressions, we use a Partial Least Squares method (PLS). Let $Z_t = (z_{1,t}; z_{2,t}; ...; z_{N,t})$ denote an $NX1$ vector of macro variables at period t. We follow Wold (1966) and Kelly and Pruitt (2013) and assume $z_{i,t}$ has a factor structure:

$$z_{i,t} = a_{i,0} + a_{i,1} MF_t + a_{i,2} ER_t + e_{i,t}. \tag{11}$$

where MF_t is the component related to changes in interest rates and ER_t is a component that is common to all macro series that is irrelevant in forecasting interest rates. The objective of the PLS method is then to estimate MF_t by imposing a factor structure on the proxy variables and to eliminate ER_t.

This method requires two steps. In the first one, for each individual macroeconomic variable Z_i, we run a time-series regression of each of these variables on a constant and a change in interest rates y_{t+12}:

$$z_{i,t} = \alpha + \beta \Delta y_{t+12} + u_{i,t}. \quad i = 1, ...N \tag{12}$$

In the second step, we run a cross-sectional regression of $z_{i,t}$ on the corresponding loading $\hat{\beta}$ estimated in the first step for each sample period:

$$z_{i,t} = \gamma + CF_t^{PLS} \hat{\beta} + v_{i,t} \quad t = 1, ...T \tag{13}$$

where CF_t is the extracted common macro factor. Essentially, the extracted macro factor is obtained by the regression coefficients of this second stage regression.

In our factor construction, we download around 100 macro and survey-based variables for the United States, United Kingdom and Germany. We obtain monthly survey variables from Consensus Economics. Further, we also collect the disagreement around these forecasts, namely the cross-sectional standard deviation from survey respondents. We transform all variables to stationarity and standardise them before running the PLS procedure.[1] Tables A.1, A.2 and A.3 in the Appendix detail the variables used in our study and the transformations used in case the series was not stationary when downloaded. The panel of variables across countries is similar, albeit not exactly identical. This is due, in some cases, to limited data availability.

We average yearly changes in interest rates across countries to obtain a global interest rate that we use as dependent variable in the first step of the PLS procedure. The Common Macro Factor (henceforth CF) is then the cross-sectional beta extracted from the second step regression. Similarly, we also compute a local country-specific factors (LF) for each country with the same method. However, in this case we use the country-specific yearly interest rate changes and only

[1] More specifically, the data from Consensus Economics reports survey forecasts for several macroeconomic variables for both the current and next calendar year. In order to approximate these survey to infer year-on-year rates, we use the procedure laid out by Camba-Méndez and Werner (2017) and Patton and Timmermann (2011).

the domestic macro variables to estimate the LF. Furthermore, we orthogonalise the local macro factors in respect to the common one:

$$LF_t = \alpha + \beta CF_t + \epsilon_t. \tag{14}$$

Namely, we extract the residuals from an OLS regression with the LF as dependent and the CF as independent variable. Orthogonalising the LF allows us to extract all the information linked to common macroeconomic developments from our local factors.

We estimate the CF in real-time by including only macroeconomic and survey data that was available at each point in time in our sample. Thus, we estimate the first time-series regression on the first eight years of data. Then, we compute the CF as the cross-sectional regression on the first-stage coefficients estimated up to that point. We repeat the procedure by increasing the sample by one month in each estimation period up to the full-sample estimates.

It is inherently complicated to give a structural interpretation of this extracted common factor, as it is a combination of a lot of different macroeconomic series. However, in order to better understand how it is formed, we regress every single variable on the factor and check the resulting R-squared (Figure 7). For example, German variables do not have a strong impact on the index, while United States and United Kingdom's measures have a stronger effect. In the United States, the biggest R^2 for the macro variables are for consumption growth, unemployment and non-farm payrolls. In the United Kingdom it's house prices, consumer confidence index, unemployment and jobless claims. In terms of surveys, real GDP growth, consumption growth and unemployment have the biggest R^2 in the United States and United Kingdom. Interestingly, the survey-based measures of disagreement have some sizable R^2 too. This entails the possibility that the CF measures, besides the current and expected macroeconomic environment, include some of the disagreement surrounding the macroeconomic outlook.

We show in Figure 6 the real-time and full sample CF together with the LF. The blue line represents the full-sample CF while the black dashed line the real time factor that we use in our paper. The real-time CF shows similar time-series behaviour to the full-sample one, but it manifests more volatility in the early 2000s and it shifts downwards more prominently during the GFC compared to the full-sample CF. Both the real-time and full-sample CF display a cyclical behaviour, as they decrease during crisis periods such as the 2001 Dot-com crash and the Global Financial Crisis (GFC). The bottom panel of the Figure shows the country-specific LF. Similarly to the CF, the United States LF shows a cyclical behaviour. The series also rebounds after the GFC and is less subdued compared to the other countries' factors during the sovereign bond crisis that hit the euro area in 2011. At the same, the LFs for Germany and the United Kingdom do not decrease markedly, at least compared to the United States LF, during the recession caused by the Dot-com bubble in the early 2000s. In general, it seems the LF is able to capture to some extent the idiosyncratic macroeconomic environment in each country and not necessarily the underlying common macro trends.

4 Quantile Regression Setup

We employ quantile regressions to characterise the conditional relationship between future bond excess returns and our estimated macro factors . Let's denote the target variable as y_{t+1}, a scalar interest rate shock whose conditional quantiles we wish to capture with our estimated macro factors. The τ th quantile of y_{t+1} is its inverse probability distribution function, denoted as

$$Q_\tau(y_{t+1}) = inf\{y : P(y_{t+1} < y) \geq \tau\}. \tag{15}$$

The quantile function may also be represented as the solution to an optimization problem

$$Q_\tau(y_{t+1}) = arg \underset{\tau}{inf} E[\rho_\tau(y_{t+1} - q)] \tag{16}$$

where $\rho_\tau(x) = x(\tau - I_{x<0})$ is the quantile loss function. As shown by Koenker and Bassett Jr (1978), the conditional quantiles of y_{t+1} are affine functions of observables x_t:

$$Q_\tau(y_{t+1}|I_t) = \beta_{\tau,0} + \beta_\tau^{'} x_t. \tag{17}$$

An advantage of quantile regression is that the coefficients $\beta_{\tau,0}, \beta_\tau^{'} x_t$ are allowed to differ across quantiles. Thus, quantile models can provide a broader picture of the target distribution when conditioning information shifts more than just the distribution's location. Further, a quantile regression differs from an OLS regression in two ways. First, it minimizes the sum of absolute errors, rather than the sum of squared errors. Second, it puts differential weights on the errors depending on whether an error term is below or above the quantile.

We evaluate forecast accuracy via a quantile R^2 based on the loss function

$$R^2 = 1 - \frac{\frac{1}{T}\sum_t [\rho_\tau(y_{t+1} - \hat{\alpha} - \hat{\beta} X_t)]}{\frac{1}{T}\sum_t [\rho_\tau(y_{t+1} - q_\tau)]}. \tag{18}$$

This expression captures the typical loss using conditioning information (the numerator) relative to the loss using the historical unconditional quantile estimate (the denominator).

In order to test the effect of our extracted Common and Local macro factors on the conditional distribution of changes in expectations and term premia, we estimate the following regression:

$$\Delta y_{t+h} = \alpha + \beta_{1,\tau} PC_t + \beta_{2,\tau} X_t + \epsilon_t \quad y = E, TP \tag{19}$$

where Δy is the 3,6 or 12 months change in either observed yields, expectations or term premia components extracted from the ATSM. X_t contains either the CF or LF. PCs are principal components extracted from the cross-section of zero-coupon yields. We calculate standard errors with a residual block bootstrap, as the autocorrelation and overlap of interest rate changes could create a bias in the standard errors that could in turn lead to distortions in the statistical inference of the results. We use a block size of 45 observations and run 1000 iterations to derive the bootstrapped standard errors. In our analysis, we focus on five empirical quantiles, specifically the 10^{th},25^{th},50^{th},75^{th} and 90^{th}. This allows us to characterize the entire conditional distribution of our target variables.

We employ this quantile regression setup to test three hyphotesis. First, we check if β_τ are statistically different from zero across quantiles, both for the CF and LF. Second, we check if β_τ differs across quantiles. We test this by comparing quantile regression coefficients and confidence bands to estimates obtained from an OLS regression with the same independent variables. Third, we focus on whether global or local factors drive some specific quantiles of these two variables.

5 Empirical Results

5.1 Changes in Yields

Figures 8 and 9 show the β^τ for the quantile regressions, where observed yields are the dependent variable and the CF and LF are the independent variables. The quantile coefficient for the CF in the left tail of the empirical distribution shown in Figure 8 is statistically different both from zero and from an OLS estimate . We can still observe this asymmetry at the six-month horizon for these two countries, but this effect dissipates with respect to the United States. Looking four quarters ahead, this asymmetry disappears. This empirical finding is not, however, present for the LF in Figure 9. Thus, the asymmetry seems driven by common macroeconomic trends rather than country-specific factors.

Table III shows the in-sample R^2 for these regressions. The table confirms the results of Figures 8 and 9. Adding the CF on top of the first three principal components extracted from yields improves the R^2 by 7pp (21.5 vs 14.5), 7.6pp (24.5 vs 16.9) and 12pp (23.9 vs 11.9) at the three-month horizon for the United States, Germany and the United Kingdom, respectively, when examining the left tail of the distribution. The R^2 of the principal components increases at longer horizons, but we can still observe further improvement in predictive power when adding the CF, even when we focus on other parts of the empirical distribution. This results confirm that the CF provides useful information that can help explain movements in interest rates, as the forecasting power improves when adding this variable. Adding the LF does not improves the R^2 of these regressions. However, as it is hard to disentangle the source of these results, we employ the interest rate decomposition obtained from our term structure model to gauge the driving force of this asymmetric effect.

5.2 Expected Rates and Term Premia Results

We show in Figure 10 the β^τ for the CF when the dependent variable is the change in the expectation component at different horizons. The upper panel shows one-quarter ahead in-sample estimates. At this horizon, there is a strong asymmetry in the impact of the CF across the distribution of the changes in expected rates. β^{τ} is statistically different both from zero and from an OLS estimate only in the left tail of the distribution. This finding is consistent across all countries. Thus, a common macroeconomic factor has sizable predictive information only for the lower quantiles of expected rate changes. A decrease in the CF by one standard deviation implies a decrease in 5-year average expected rates by 28 bps for the United States, 20 bps for Germany and 40 bps for the United Kingdom. As shown in Table I, that is an approximate change of 1.0, 0.5 and 0.7 standard deviations in the target variable, respectively. To put these results into perspective, the CF decreases by around 2.5 standard deviations during the Great Financial Crisis. A change of this magnitude implies a very strong effect on expected rates one quarter ahead. According to these results, our common macroeconomic factor can predict large negative changes in expected rates, which usually occur during major recessions. This happens when the central bank aggressively eases its monetary policy stance in order to contain the macroeconomic fallout of a recessionary period.

At the same time, the CF offers no predictive power about the upper quantiles of future changes in expected rates. This happens when expected rates rise during a tightening in monetary policy (the right tail of the distribution). The asymmetric effect on the left tail is still significant at the six- and twelve-month horizons, although at the longer horizon the effect is statistically different from an OLS for the United States and United Kingdom only at the 10% level. One-year ahead, β^{τ} are significant across the entire distribution, although the slope of these coefficients is still downward when moving towards the right tail. While it is still possible that macroeconomic factors affect expected rates at this longer horizon, it is important to gauge whether this effect fades when attempting to forecast expected rates out-of-sample. Figure 23 in the Appendix shows the same results when we substitute the CF with the country-specific LF. In this case, the asymmetry we discussed above disappears, as all β^{τ} are not statistically different from OLS estimates. However, there are a few instances where the coefficients are statistically different from zero, especially for Germany. This might be partially explained by how our CF and LF are constructed. As I showed in Figure 7, German macroeconomic variables and surveys appear to load less on the CF. Thus, it is possible that this phenomenon drives this result. Another possibility is linked to the status of German Bunds, which are considered – especially since the GFC as the "safe haven" in the euro-area bond market. Thus, a deterioration in the German macroeconomic environment could be related to a deterioration in the overall outlook for the Eurozone, which in turn could explain this effect on expected rates.

Table IV shows the in-sample R^2 of the regressions above. The second row in each panel demonstrates the extent to which adding the CF improves the forecast. At the three-month horizon, adding the CF to the regression markedly improves the left-tail forecasts compared with a regression where only the first three PCs are used as explanatory variables. Specifically, the R^2 almost doubles for the United States (26.1 vs 13.2) and for Germany (26 vs 12.8) and almost triples for the UK (33.4 vs 13.1) for the United Kingdom. The improvement in the forecast deteriorates the more we move to the upper quantiles, but in general the accuracy improves across the distribution when adding the CF to the regressions. Adding the LF instead of the CF (the third row in each panel) does not substantially improve the R^2 consistently compared with a quantile regression using only PCs. We show in Figures 15 and 16, the entire time-series of the empirical distribution when we add the CF as independent variable. In both figures, the asymmetry between the left and right tails of the conditional density is clearly visible. The lower quantiles vary significantly over time, while the upper quantiles are stable.

Finally, we fit non-parametric distributions similarly to Mitchell et al. (2022) in order to smooth the quantile function and recover a probability density function. As the quantile regressions can provide approximate estimates of the quantile function, which is an inverse cumulative distribution function, it can be complicated to map these estimates into a probability distribution because of approximation error. Thus, we can use this methodology of Mitchell et al. (2022) to recover a probability density function (pdf). Figure 17 and 18 plot three versions of the conditional PDFs of forecasts of expected rates for October 2008 one and four-quarter ahead. October 2008 was the month in which several central banks acted simultaneously to ease global monetary conditions at the onset of the GFC.[2] The blue dashed line shows distributions conditional on PCs only, while the red lines add the CF as conditioning variable. The black vertical line represents the actual realised change in expected rates. The result of this exercise is striking. The distribution conditional both on PCs and CF displays greater probability mass on the left tail, especially at the longer horizon. More speciically, at the 3-months horizon the densities in which we add the CF as conditioning variable have bigger skewness on the left tail. While the density mass for the PCs-only results is more concentrated around the zero, adding the CF shifts the distribution to the left, in line with the realised change in expected rates. At the longer horizon, the result is even more striking. While the PCs fail to capture the future variation in expected rates, the density implied by the PCs+CF shifts the location of the conditional distribution and to the left and shows greater negative skewness on the left tail of the distribution. In Figures 19, 20 and 21 we also show how the evolution of one-quarter-ahead estimated densities over our sample. Here, we can clearly observe the change in downside risk for expected rates in the densities in which the CF is added as a conditioning variable. This is striking during recession periods, in which the skewness of the conditional density increases markedly more compared with densities in which principal components are the only explanatory

[2] https://www.federalreserve.gov/newsevents/pressreleases/monetary20081008a.htm

variables. Further, this time-series behaviour can be observed in all three countries. Taken together, these results illustrate the strong effect that a common macroeconomic factor has on the conditional distribution of expected rates.

Figure 14 shows the same regressions, but with changes in term premia instead of changes in expected rates as dependent variables. Here, the asymmetry in expected rates that we captured previously disappears. The β_τ for the CF are almost never statistically different from an OLS estimate, and only in some cases from zero. The few exceptions are for the right tail of the United States one quarter ahead and for some quantiles for the United Kingdom, especially six and twelve months ahead. We can also relate our results to the forecasting regression typically used in the macro-spanning puzzle we described previously. Although most of these regressions are some sort of OLS with robust or bootstrapped standard errors, our β_τ for the median quantile is the closest result to this kind of model. The median coefficient for the CF loads positively on expected rates in Figure 10 and negatively on the corresponding term premia coefficient in Figure 14. Thus, regressions in which the results show that macroeconomic information does not have a strong effect on nominal yields could be driven by the opposite loadings in these two components as also shown by Duffee (2011). Even if in this instance we did not capture the asymmetric effects that we observed for expected short-term rates, the pattern that emerges from these regressions can tell us something about the usual macro-spanning predictive regressions. In fact, the estimated quantile coefficients are never significant throughout the entire conditional empirical distribution. This raises the possibility that the significant results in the literature that point to the presence of unspanned factors are actually driven by a few data points – big swings in each direction for term premia – instead of the entire sample. Thus, analysing possible non-linear effects of these unspanned variables is warranted. We also show in

Table A.4 in the Appendix the R^2 of these regressions. The table confirms the results we show in Figure 14 and 25. The CF does not perform better than the PCs or the LF in almost all specifications. This suggests movements in term premia that are more driven by country-specific macroeconomic dynamics compared with the results for the expectations component, in which a common macroeconomic factor yields powerful results on the movements of these components in these three countries.

5.3 The Role of Yield Based Factors

We show in Figure 11, 12 and 13 how the coefficients for the level, slope and curvature factors extracted from the yield curve vary across quantiles for the three months ahead expected rates regressions in each country. In these figures we show the same coefficients from the same regressions for the CF. These are similar results to the ones we showed in Figure 10, but without averaging across maturities. The level factor does show asymmetric effect for Germany and the United Kingdom, both at the 10th and 90th quantile. For these two countries, the curvature factor also displays asymmetric effects (at the 10th quantile for Germany and the 90th for the UK). Further, the slope factor has asymmetric effects at the 90th quantile for the UK. At the same time, the US yield-based factors do not display asymmetric effects in these regressions, as the quantile betas are never statistically different from the OLS coefficients.

It appears that for Germany and the UK, PCs have asymmetric effects during both easing and tightening cycle. However, the CF still manages to dominate the PCs at the 10th quantile across the entire spectrum of maturities. When looking at large positive changes in one quarter ahead expected rates, the PCs clearly dominate the CF and can explain the time-variation in expected rates without the help of the CF. In this context, it is clear that during tightening cycles, macroeconomic information is more likely to be embedded in in the yield curve, and thus adding a macroeconomic factor does not help in predicting yield curve movements. We do not find the same results for the United States, as 90th quantile coefficients for the level, slope and curvature factor are not almost always not significant. The curvature factor is significantly different from zero for the 1-year maturity, but it is very similar to the OLS estimates

5.4 Out-of-Sample Results

We replicate the analysis carried out in the previous section, but use only real-time information to build the conditional forecast.[3] We use the first nine years of our sample to estimate the starting coefficients and then recursively estimate the model up to the end of the sample (2019-12). We construct a conditional distribution starting in March 1999 by using data up to December 1998. Then, we iterate the same regressions by expanding the estimation sample one month at a time. In order to assess the out-of-sample performance of our model, we look at the out-of-sample pseudo-R^2 and then compare the conditional out-of-sample quantiles with the in-sample ones.

We first focus our out-of-sample analysis on the results for expected rates, where our in-sample results showed the asymmetric impact of the CF on the conditional distribution. Table V shows the out-of-sample R^2 for the CF and the LF when projected onto changes in expected rates. The R^2 can be negative in case the historical unconditional quantile has better predictive ability than the conditional quantile. The asymmetric predictive ability of the CF that we showed with the in-sample results is still observable. For example, adding the CF increases the R^2 of the left tail at the three month horizon by 23.5pp (7.5 vs -16) for the United States, 17.1pp (7 vs -10.1) for Germany and 38.9pp (26.7 vs -12.2) for the United Kingdom. This improvement

[3] We used revised macroeconomic data in my analysis. Surveys from Consensus Economics are instead not revised.

is also visible at the six-month horizon. One year ahead, the forecast improves. If we focus on the other quantiles, adding the CF sometimes improves the forecast compared with a model using the PCs as the only conditioning variables, but it still performs more poorly than an unconditional forecast. Similar to the in-sample results, the LF fares worse than the CF and than a predictive regression only with the PCs as conditioning variables at all horizons.

We show the same out-of-sample forecasts for the changes in term-premia in Table A.5 in the Appendix. Here, the performance of the CF is abysmal, as it performs worse than the unconditional quantile in most of the forecasts. Only using PCs yields better results in most cases. The LF performs better than the CF in many instances, but it does not appear to consistently improve the forecast above and beyond either the PCs or the historical unconditional quantiles.

In Figure 22 we show the in- and out-of-sample predicted quantiles for the changes in expected rates. In this figure, the in-sample and out-of-sample quantile estimates are very similar, especially for the period of the GFC, during which expected rates decreased markedly due to the monetary policy response to the crisis. This event is not in the real-time data when estimating out-of-sample, but it is still captured by the conditional quantiles. Overall, the out-of-sample results confirm that the asymmetry of the response of expected interest rates to a common macro factor can be detected in real time.

6 Robustness Tests

We perform several robustness tests on our findings. First, we run the same quantile regressions described above for expected rates, but we add more yield-based pricing factors as independent variables. We use the first five PCs extracted from yields instead of the first three. It is possible that macroeconomic information is hidden in factors other than the level, slope and curvature of interest rates. In Figure B.1 in the Appendix, we show that adding further PCs does not affect our results for the effect of the CF on expected rates.

It is also possible that how we estimate the CF and the LF materially affects our results. Thus, we estimate the same quantile regressions of the previous section, but we use two different macroeconomic measures in place of the CF. First, we proxy the CF with the Chicago Fed National Activity Index (CFNAI), which is estimated to gauge overall economic activity and related inflationary pressure in the United States. This is not a factor common to all countries, but assuming the United States has a stronger effect on the global macroeconomic environment compared with Germany and the United Kingdom allows us to imperfectly proxy the CF with this variable. Figure 26 in the Appendix shows that using the CFNAI makes our results somewhat weaker. We still observe the asymmetry of the impact of this macro variable in the United States and United Kingdom up to a six-month horizon, but this effect disappears four quarters ahead. Moreover, this asymmetry is not present for Germany. However, it is possible that the CFNAI, being a very United States-specific index, fails to capture all the global macroeconomic developments.

We also extract the first principal component from the cross-section of our macro variables and utilise it in the regressions instead of the CF. This component only explains 29% of the cross-sectional variation; thus, it is possible it will perform more poorly than the CF estimated from the Partial Least Squares approach. Figure 27 shows the results of this exercise. This macro variable is significantly different from an OLS for the United Kingdom and Germany at the three-month horizon and only at the six-month horizon for the United States. Even if the results are weaker with this estimation, the same asymmetric pattern we observed with the CF emerges from this exercise.

7 Conclusion

In this paper we study the conditional distribution of the changes in the expectations and term premia components of interest rates. We show that a common macroeconomic factor has predictive ability for the left tail of interest rate expectations in several countries. The effect of this common macroeconomic factor is economically large, and it can forecast big negative changes in expected rates in and out-of-sample. We also show how this factor affects the conditional distribution of expected rates by changing its conditional skewness and variance. At the same time, this factor does not show predictive ability for the distribution of term premia. Our results also offer another perspective on how macroeconomic information might be embedded in the yield curve at different points in time, and how this relates to the perceived monetary policy reaction function of the central bank.

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8 Figures

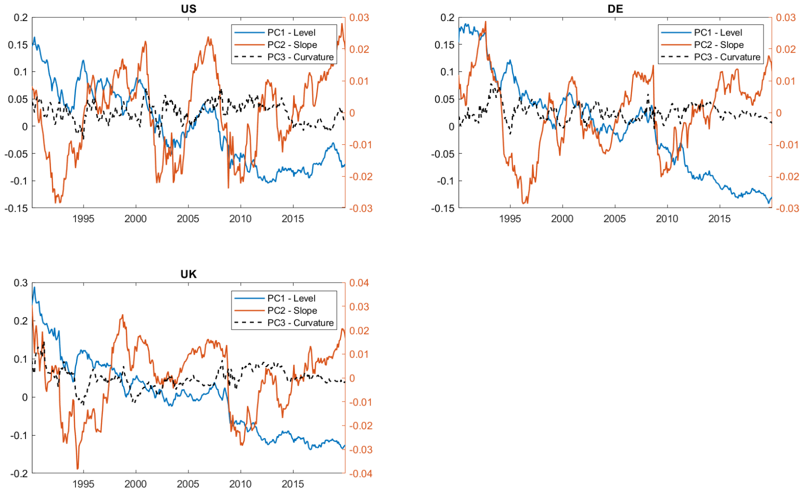

Figure 2: Principal Components extracted from yields
First three principal components (PCs) extracted from US, DE and UK yields. The blue line shows the level factor, the orange line the slope factor and the dashed black line the curvature factor.

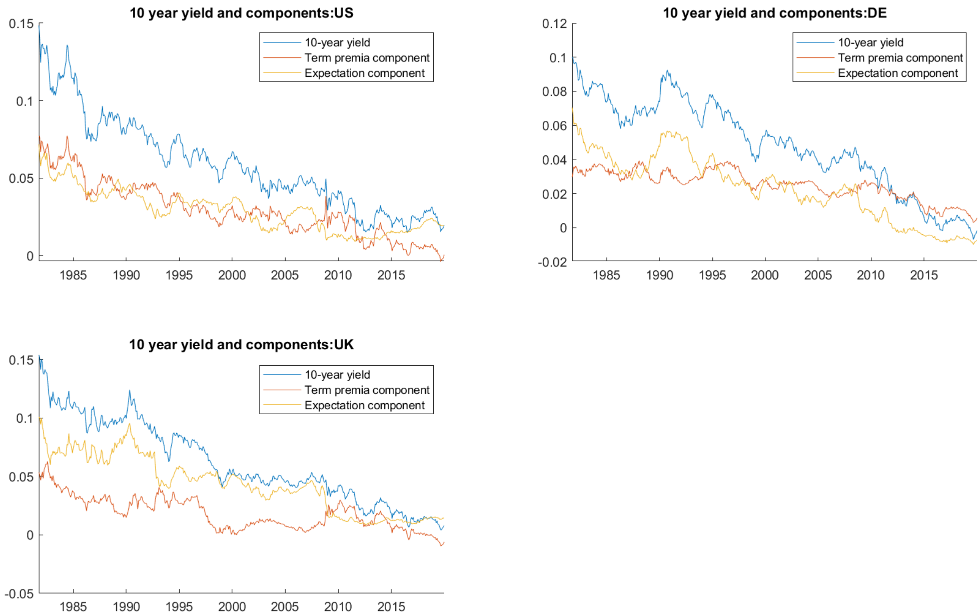

Figure 3: 10-year yields, expectations and term premia
Expectations and term premia components are estimated thanks to an affine dynamic term structure model (ATSM). The components shown in the chart are full-sample estimates (1980-01, 2019-12).

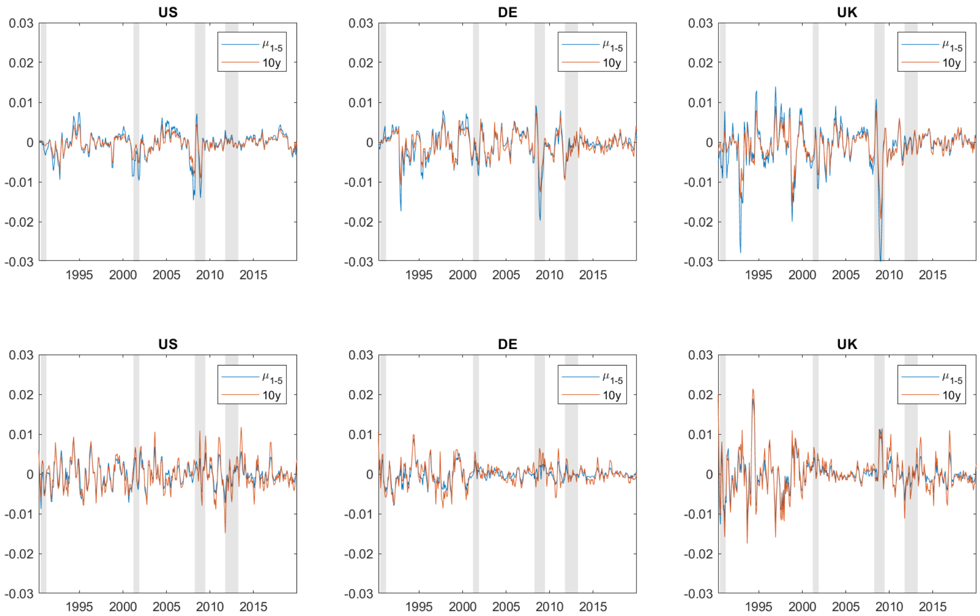

Figure 4: 3-month changes in expectations and term premia
The top panel shows 3-month changes in the expectation component, while the bottom panel shows 3-month changes in the term premia component. Grey shaded lines are recession periods obtained by CEPR. The blue line is the average change in the yields component for yields between 1 and 5 years. The orange line is the change in the 10-year components.

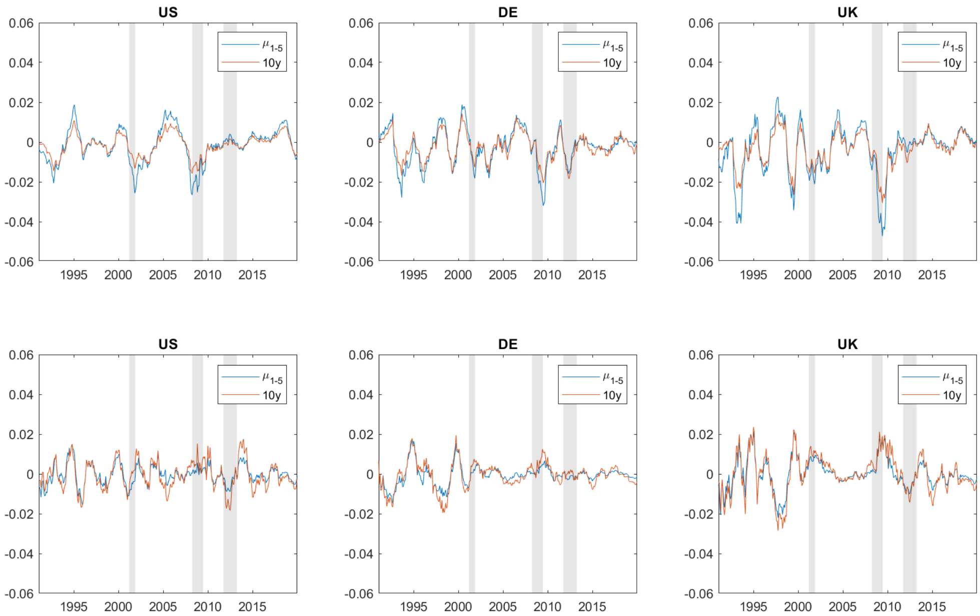

Figure 5: 12-month changes in expectations and term premia

The top panel shows 12-month changes in the expectation component, while the bottom panel shows 12-month changes in the term premia component. Grey shaded lines are recession periods obtained by CEPR. The blue line is the average change in the yields component for yields between 1 and 5 years. The orange line is the change in the 10-year components.

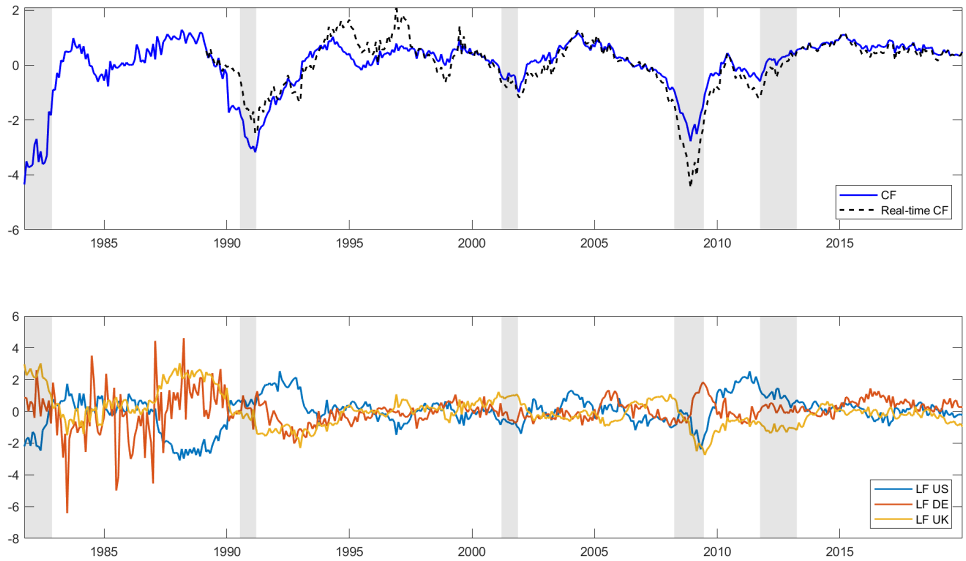

Figure 6: Common and Local Macro Factors

The top panel shows the full-sample (blue line) and real-time (black dashed line) common macro factor extracted from around 100 macroeconomic variables for the US, The bottom shows the country-specific local factors that are orthogonalised in respect to the common factor. Grey shaded lines are recession periods obtained by CEPR

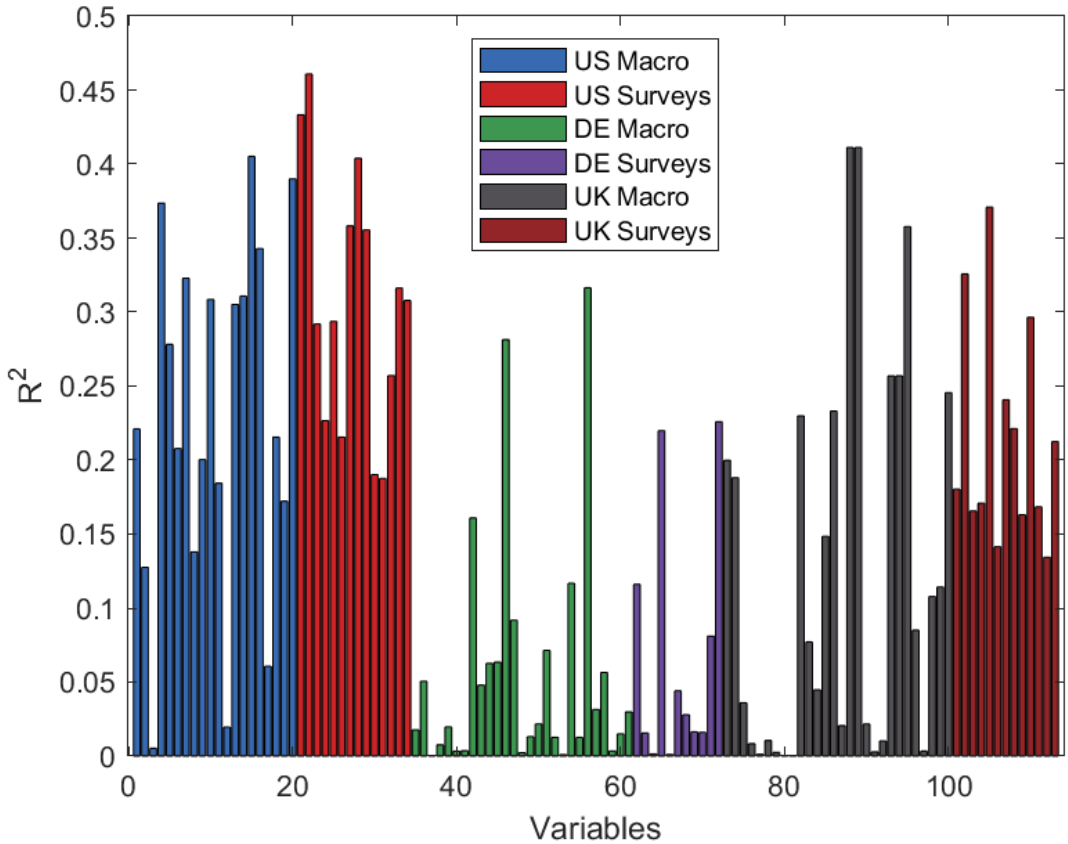

Figure 7: R^2 of regressions of single macro variables on the common macro factor
R^2 of univariate regressions in which the dependent variable is the CF and the independent variable is every single macroeconomic series that are part of the CF. the variables for each country are divided in macroeconomic variables and surveys of economic variables obtained from Consensus.

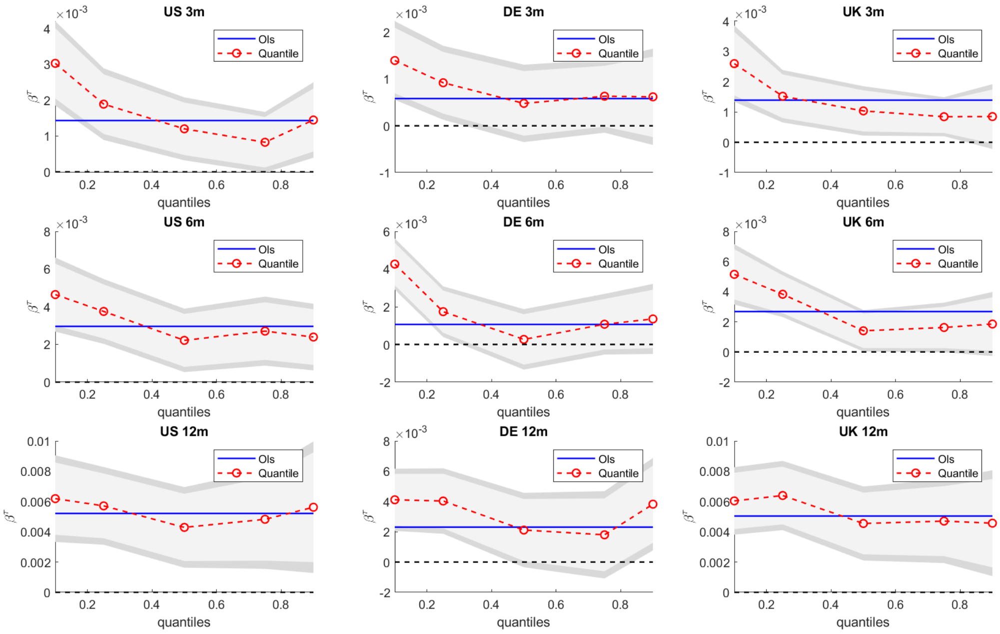

Figure 8: Beta of OLS and quantile regressions for CF - observed yields

Each Column shows OLS and quantile regression betas at different horizons for each country. The black dashed line represents the zero. The blue solid line shows the Beta from an OLS regression. The red dashed line with circles shows the β^τ obtained from quantile regressions for five different quantiles. The dependent variable of the OLS and quantile regressions are 3,6 or 12 month changes in observed zero-coupon yields. The independent variables are the first three Principal Components extracted from yields (PCs) and the Common Macro Factor (CF). Grey shaded bands for the quantile regression Betas are obtained through a residual block bootstrap with an N=45 block size.

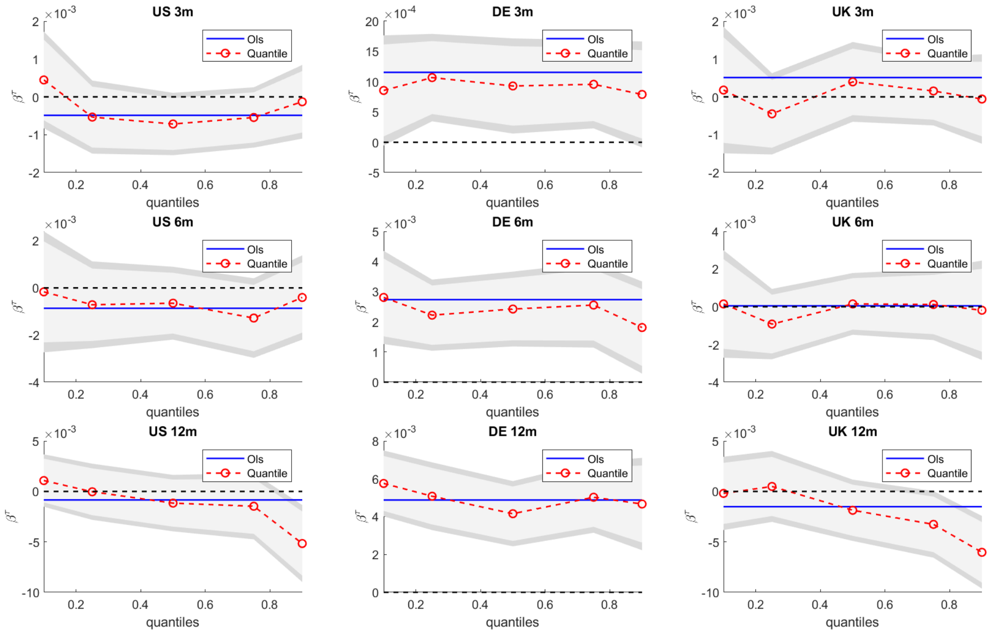

Figure 9: Beta of OLS and quantile regressions for LF - observed yields
Each Column shows OLS and quantile regression betas at different horizons for each country. The black dashed line represents the zero. The blue solid line shows the Beta from an OLS regression. The red dashed line with circles shows the β^{τ} obtained from quantile regressions for five different quantiles. The dependent variable of the OLS and quantile regressions are 3,6 or 12 month changes in observed zero-coupon yields. The independent variables are the first three Principal Components extracted from yields (PCs) and the Common Macro Factor (CF). Grey shaded bands for the quantile regression Betas are obtained through a residual block bootstrap with an N=45 block size.

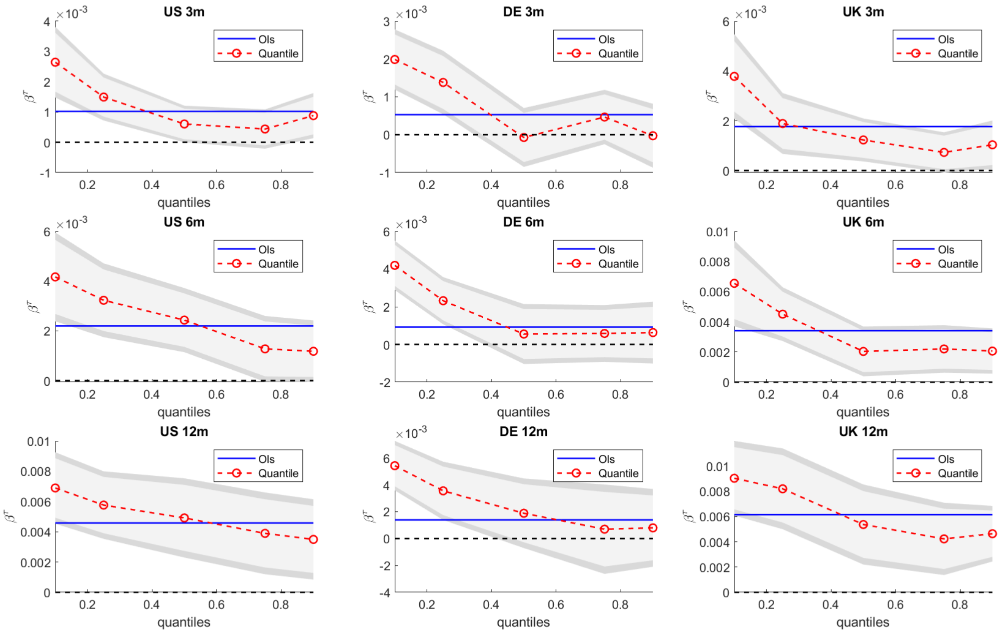

Figure 10: Beta of OLS and quantile regressions for CF - expectation component
Each Column shows OLS and quantile regression betas at different horizons for each country. The black dashed line represents the zero. The blue solid line shows the Beta from an OLS regression. The red dashed line with circles shows the β^{τ} obtained from quantile regressions for five different quantiles. The dependent variable of the OLS and quantile regressions are 3,6 or 12 month changes in the expectations component. The independent variables are the first three Principal Components extracted from yields (PCs) and the Common Macro Factor (CF). Grey shaded bands for the quantile regression Betas are obtained through a residual block bootstrap with an N=45 block size.

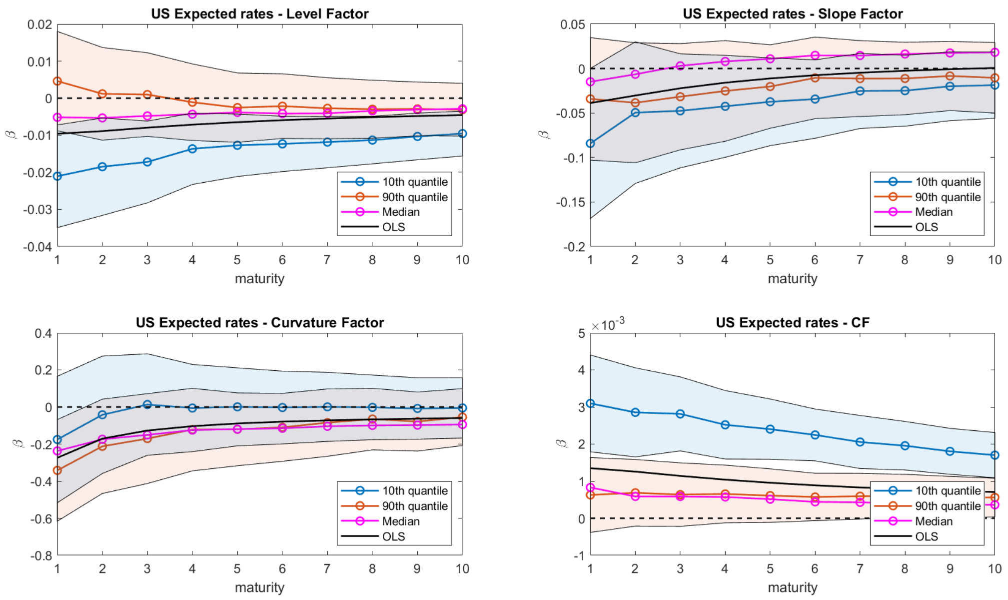

Figure 11: Betas of PCs and CF by maturity - 3m ahead US expected rates
The black line represents the Beta for OLS regressions at each maturity. The blue, orange and cyan dotted lines show the 10th, 90th and 50th quantile betas, respectively. The top and bottom left panel show the coefficients for the first 3 principal components (PCs) of yields, while the bottom right panel shows the same coefficients for the CF.

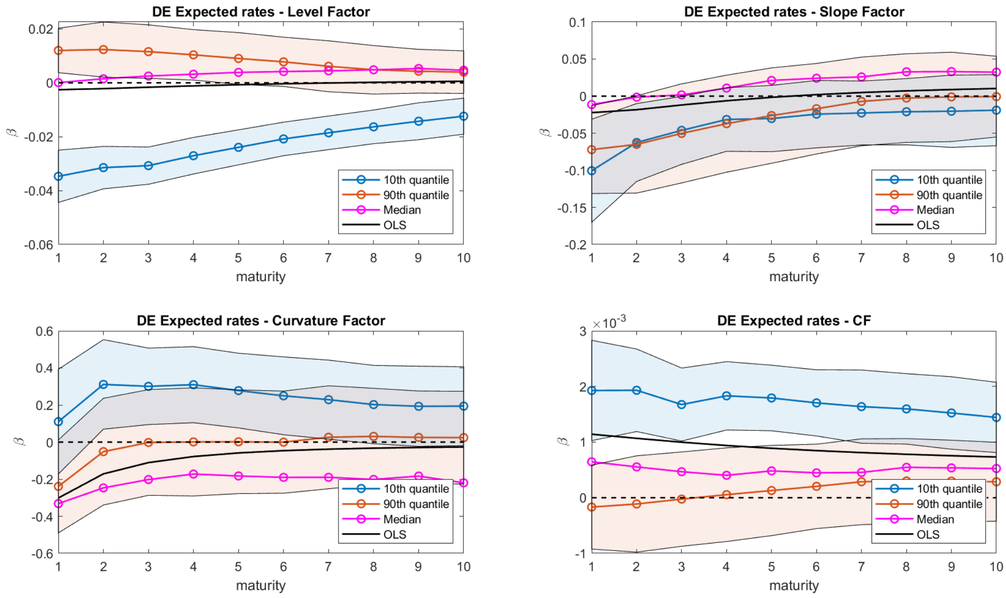

Figure 12: Betas of PCs and CF by maturity - 3m ahead DE expected rates

The black line represents the Beta for OLS regressions at each maturity. The blue, orange and cyan dotted lines show the 10th, 90th and 50th quantile betas, respectively. The top and bottom left panel show the coefficients for the first 3 principal components (PCs) of yields, while the bottom right panel shows the same coefficients for the CF.

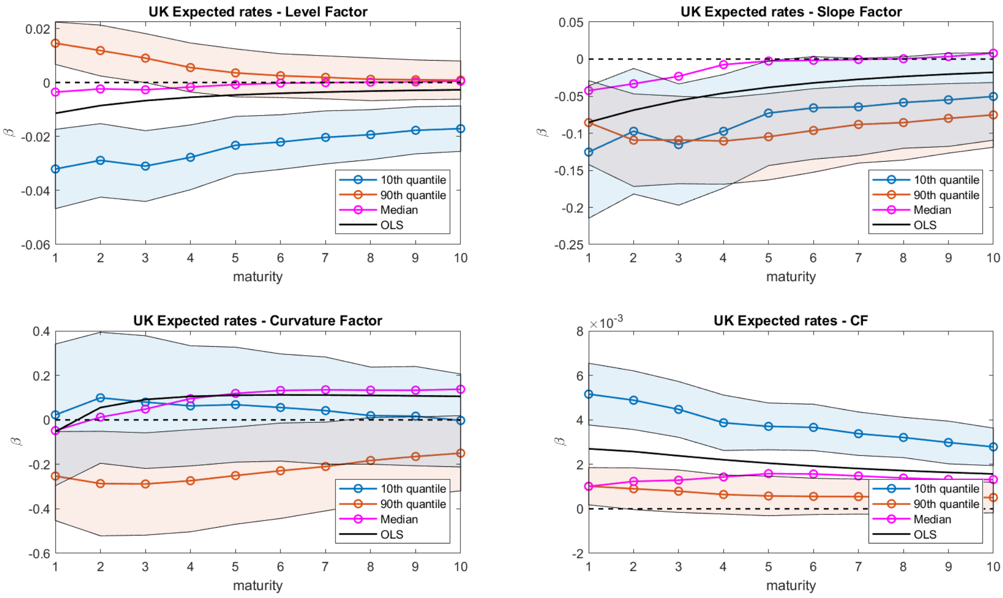

Figure 13: Betas of PCs and CF by maturity - 3m ahead UK expected rates
The black line represents the Beta for OLS regressions at each maturity. The blue, orange and cyan dotted lines show the 10th, 90th and 50th quantile betas, respectively. The top and bottom left panel show the coefficients for the first 3 principal components (PCs) of yields, while the bottom right panel shows the same coefficients for the CF.

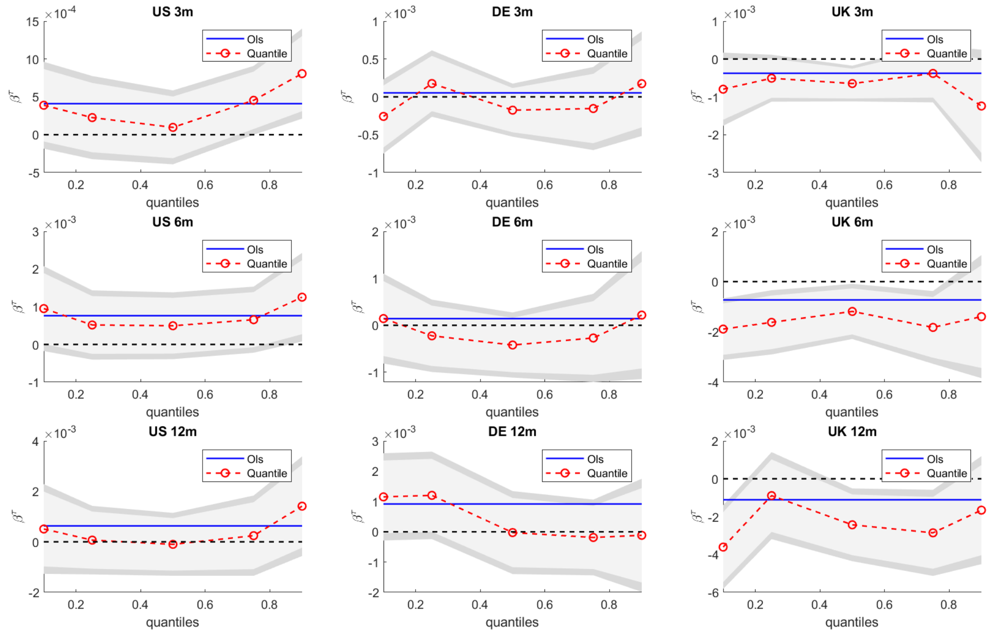

Figure 14: Beta of OLS and quantile regressions for CF - term premia component
Each Column shows OLS and quantile regression betas at different horizons for each country. The black dashed line represents the zero. The blue solid line shows the Beta from an OLS regression. The red dashed line with circles shows the β^{τ} obtained from quantile regressions for five different quantiles. The dependent variable of the OLS and quantile regressions are 3,6 or 12 month changes in the term premia component. The independent variables are the first three Principal Components extracted from yields (PCs) and the Common Macro Factor (CF). Grey shaded bands for the quantile regression Betas are obtained through a residual block bootstrap with an N=45 block size.

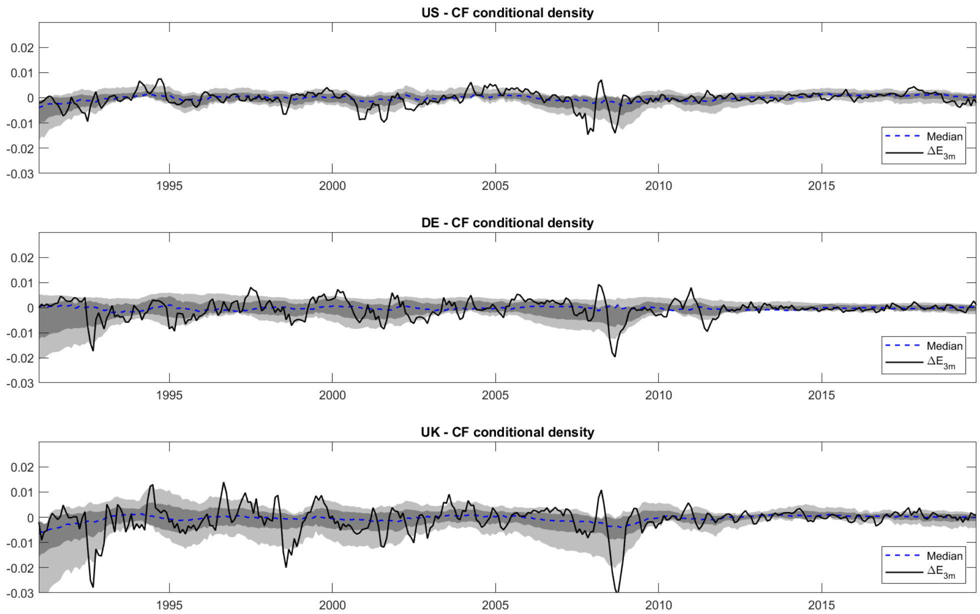

Figure 15: Conditional Distribution 3 months ahead - expectations component

Each chart shows the conditional density of one of the countries in our study.The black line shows the realised 3 months change in the expectation component. The blue dashed line shows the conditional median. The dark and light grey shaded areas represent the conditional interquartile range and the 10th and 90th quantile, respectively. The conditional density is obtained through quantile regressions with the Principal Components (PCs) and the Common Factor (CF) as independent variables.

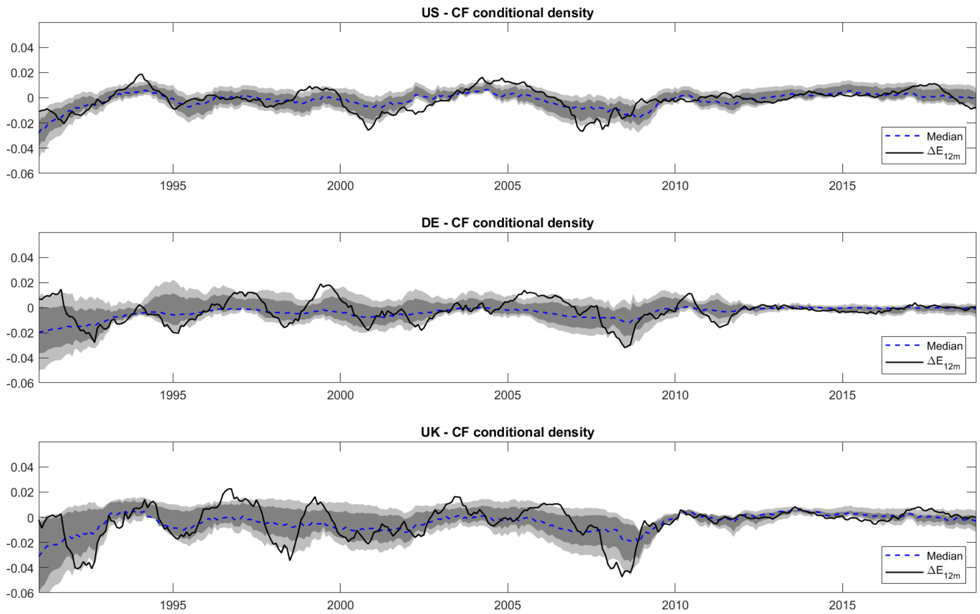

Figure 16: Conditional Distribution 12 months ahead - expectations component

Each chart shows the conditional density of one of the countries in our study.The black line shows the realised 12 months change in the expectation component. THe blue dashed line shows the conditional median. The dark and light grey shaded areas represent the conditional interquartile range and the 10th and 90th quantile, respectively. The conditional density is obtained through quantile regressions with the Principal Components (PCs) and the Common Factor (CF) as independent variables.

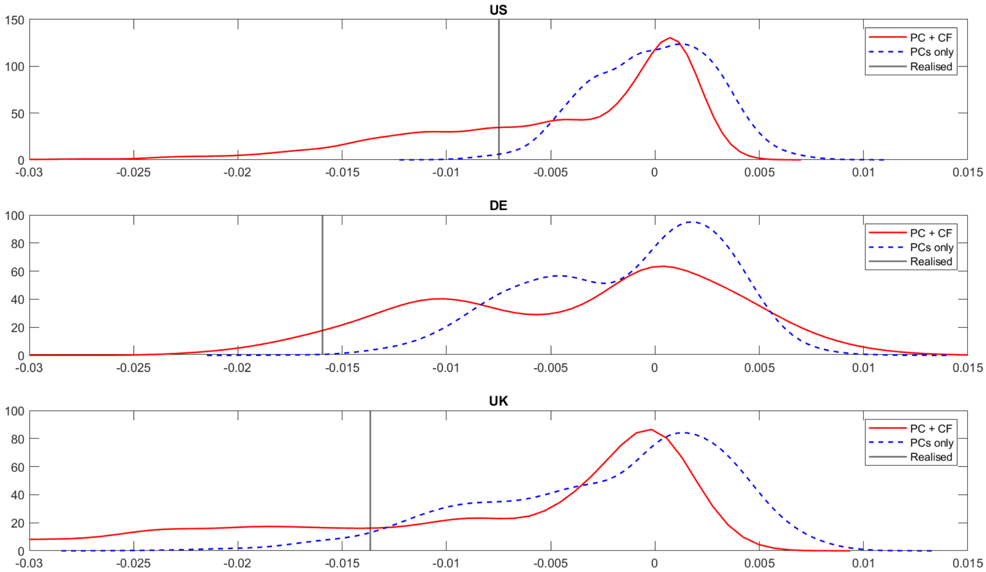

Figure 17: Expected rates one quarter ahead in July 2008
Densities are for 3-month ahead expectation component in July 2008. Blue line is a conditional density from quantile regressions with PCs as the only independent variables. Red and blue dashed lines are quantile regressions in which independent variables are PCs and PCs+CF, respectively.

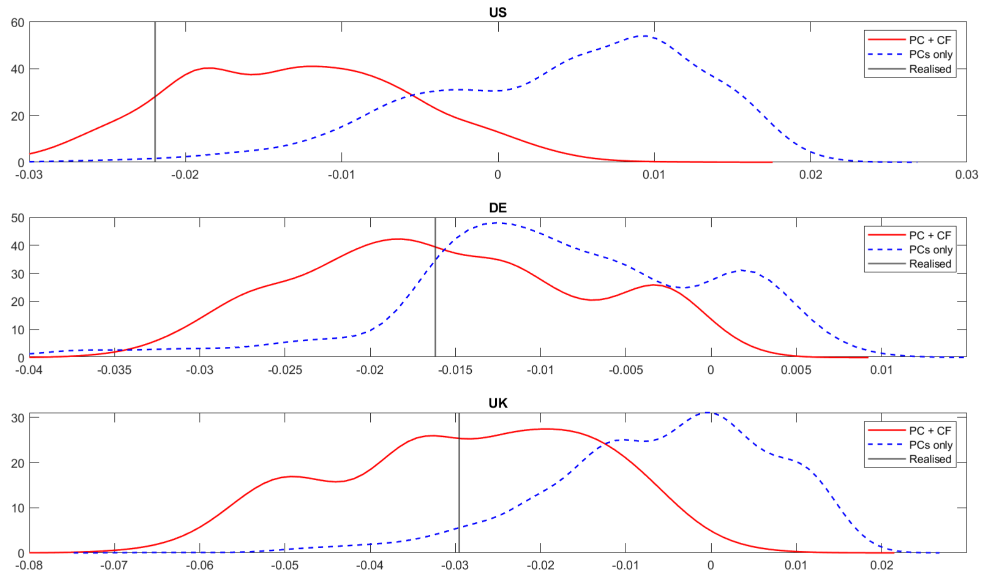

Figure 18: Expected rates four quarters ahead in October 2007
Densities are for 12-month ahead expectation component in October 2007. Blue line is a conditional density from quantile regressions with PCs as the only independent variables. Red and blue dashed lines are quantile regressions in which independent variables are PCs and PCs+CF, respectively.

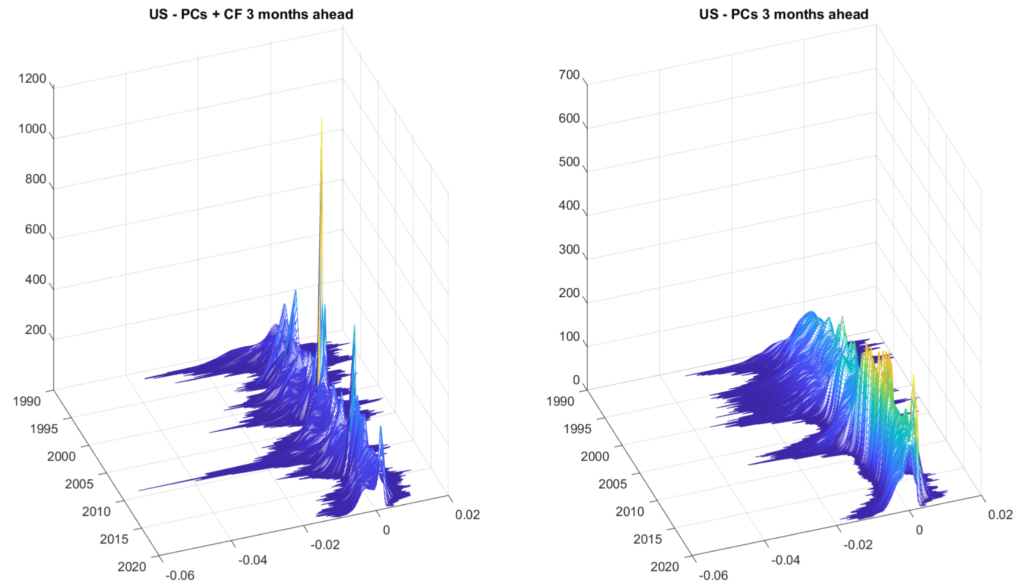

Figure 19: Predictive distribution for expected rates - United States
3 months ahead predictive distribution of expected short-term rates. The left-hand chart is based on quantile regressions with the CF and PCs as conditioning variables. Right-hand chart has only PCs as conditioning variables.

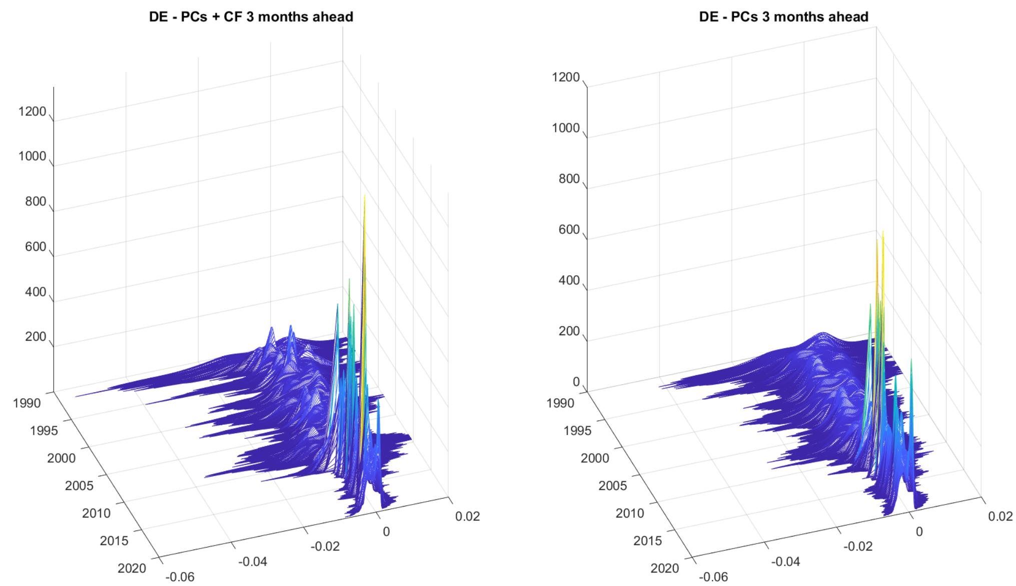

Figure 20: Predictive distribution for expected rates - Germany
3 months ahead predictive distribution of expected short-term rates. The left-hand chart is based on quantile regressions with the CF and PCs as conditioning variables. Right-hand chart has only PCs as conditioning variables.

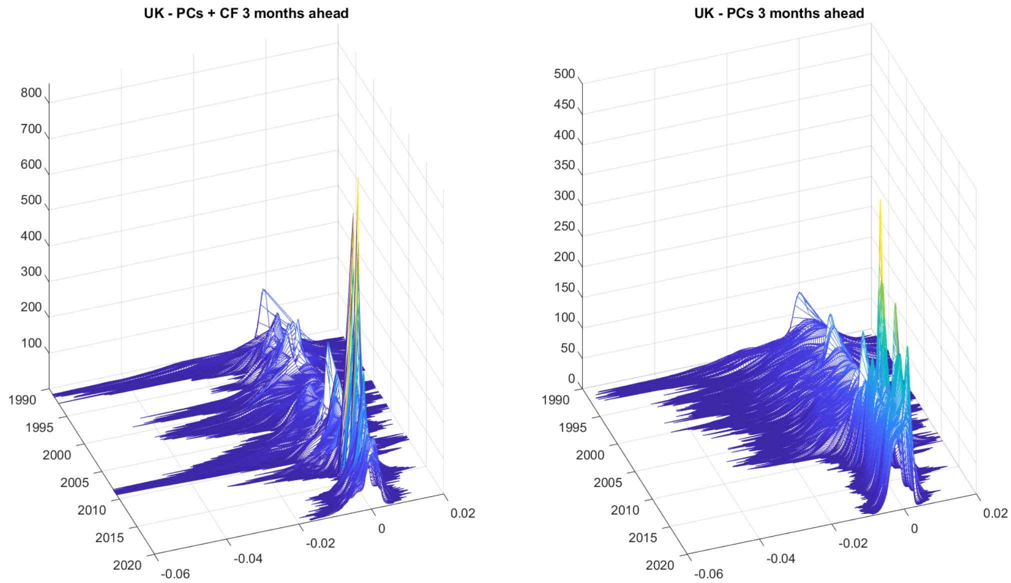

Figure 21: Predictive distribution for expected rates - United Kingdom
3 months ahead predictive distribution of expected short-term rates. The left-hand chart is based on quantile regressions with the CF and PCs as conditioning variables. Right-hand chart has only PCs as conditioning variables.

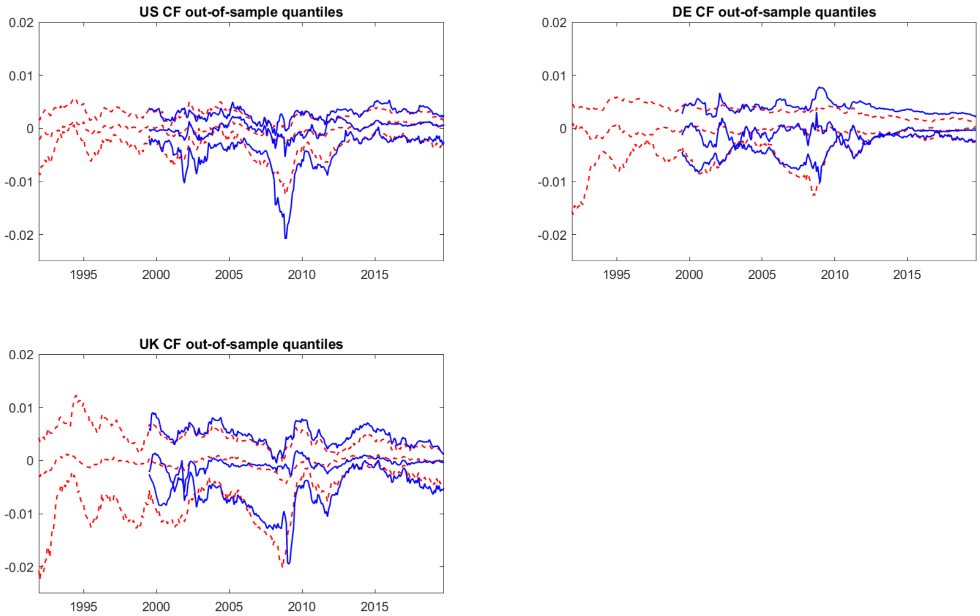

Figure 22: Out of sample predictions - 3 months ahead
The figure compares out-of-sample and in-sample predictive densities of the changes in the expectations component 3 month ahead. The red dashed line and blue line show the in-sample and out-of-sample conditional density, respectively.

9 Tables

	US				DE				UK			
	μ	σ	Min	Max	μ	σ	Min	Max	μ	σ	Min	Max
ΔE_{3m}	-4.3	31.6	-146.1	74.8	-6.5	38.0	-197.3	92.0	-10.0	56.4	-311.8	139.6
ΔTP_{3m}	-1.3	28.3	-87.9	93.6	-1.3	21.0	-80.0	89.0	0.0	39.0	-126.8	189.8
ΔE_{12m}	-16.5	86.6	-265.4	186.4	-26.4	89.7	-319.5	187.7	-39.1	127.3	-472.7	225.7
ΔTP_{12m}	-4.8	50.2	-153.4	141.6	-6.3	48.1	-148.9	170.7	-0.3	75.2	-220.1	210.4
PC1	0.06	6.96	-10.40	16.41	0.11	8.82	-14.21	18.84	0.11	9.82	-13.79	28.87
PC2	-0.02	1.33	-2.85	2.81	-0.01	1.18	-2.87	2.88	-0.02	1.38	-3.83	3.04
PC3	0.00	0.31	-0.85	0.77	0.00	0.26	-0.68	0.91	0.00	0.42	-1.16	1.52
CF	0.00	1.00	-4.15	1.37	0.00	1.00	-4.15	1.37	0.00	1.00	-4.15	1.37
LF	0.00	1.00	-4.07	2.44	0.00	1.00	-4.29	3.80	0.00	1.00	-4.03	2.09

Table I: Summary Statistics

The table shows the summary statistics for the main variables in our study. ΔE and ΔTP are calculated as basis points changes of 5-year average short-term rate expectations and term premia over a 3 and 12-months horizons. PC1, PC2 and PC3 are the first three principal components extracted from yields. CF and LF are the common and local macro factors estimated by around 120 macro series.

Observed yields							
	Δy_3				Δy_{12}		
	US	DE	UK		US	DE	UK
US	1	0.55	0.45	US	1	0.62	0.54
DE	0.42	1	0.60	DE	0.35	1	0.69
UK	0.46	0.68	1	UK	0.57	0.72	1

Table II: Correlations

Cross-country correlations below the diagonal are for the expectations component, while correlations above the diagonal are related to term-premia. The left matrix represents the cross-country correlations for 3-month changes in the expectation and term-premia, while the right matrix shows the same correlations for 12-month changes.

	US					DE					UK				
	Δy_{3m}					$\Delta y3m$					Δy_{3m}				
Quantile	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
PCs	14.5	9.0	1.8	0.4	3.0	16.9	9.9	0.3	1.9	2.9	11.9	6.1	2.0	0.3	2.6
PCs+CF	21.5	12.4	2.7	1.1	4.8	24.5	13.0	2.2	2.7	3.3	23.9	12.5	5.3	1.1	2.6
PCs+LF	14.6	10.2	3.2	1.1	3.2	21.1	12.8	1.9	2.6	3.2	12.0	6.1	2.3	0.4	2.6
	Δy_{6m}					Δy_{6m}					Δy_{6m}				
PCs	13.5	11.0	6.0	2.2	3.2	19.7	14.8	2.3	2.0	4.0	13.7	6.9	4.5	0.5	1.0
PCs+CF	24.5	17.8	9.6	3.7	5.1	31.6	18.4	3.4	3.8	4.6	29.9	14.3	7.9	1.7	2.1
PCs+LF	13.7	12.4	6.7	3.6	3.6	25.3	18.9	6.0	6.2	7.5	13.7	7.0	4.7	0.8	1.1
	Δy_{12m}					Δy_{12m}					Δy_{12m}				
PCs	24.0	18.7	10.1	3.2	1.2	28.5	21.9	5.5	1.2	1.1	26.8	13.5	6.1	2.6	1.5
PCs+CF	30.6	26.1	15.5	7.6	3.8	38.6	26.8	7.9	4.4	6.7	37.8	21.8	11.3	5.3	4.6
PCs+LF	24.7	18.7	10.9	3.8	1.7	34.5	28.7	13.2	10.9	14.9	27.0	13.7	6.5	5.3	7.0

Table III: R^2 of quantile regressions at different horizons for observed yields
Columns 2-6 shows the in-sample results for the US, Columns 7-11 for DE and Columns 12-16 for the UK. Each panel represents a different horizon, with the top one showing results 3 months ahead, the middle one six months ahead and the bottom one 12 months ahead. The dependent variable in each panel is the average change in observed yields at the relevant horizon. For each horizon, I show the R^2 of three different specifications. The first one is a quantile regression with PCs as the only independent variable, while the second and third ones show results for regression in which I add either the CF or the LF on top of the PCs.

	US					DE					UK				
	ΔE_{3m}					ΔE_{3m}					ΔE_{3m}				
Quantile	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
PCs	13.2	6.2	5.2	4.3	7.6	12.8	8.0	1.4	5.4	5.5	13.1	7.9	1.0	2.1	8.9
PCs+CF	26.1	11.8	7.4	5.8	9.9	26.0	14.3	2.5	6.4	5.6	33.4	16.6	3.9	3.9	11.5
PCs+LF	13.4	6.5	5.3	4.4	8.2	13.8	8.5	1.9	5.6	5.7	16.7	8.8	1.1	2.7	11.1
	ΔE_{6m}					ΔE_{6m}					ΔE_{6m}				
PCs	14.5	11.3	6.2	8.2	14.1	16.2	15.7	3.0	6.5	8.3	17.6	13.2	1.8	3.1	11.6
PCs+CF	31.9	21.3	10.2	12.0	17.7	32.4	21.7	6.3	7.9	8.6	36.4	24.1	8.3	7.3	15.7
PCs+LF	15.5	11.4	6.2	8.3	14.4	18.2	16.4	3.9	8.8	10.1	21.1	14.2	2.0	4.9	15.2
	ΔE_{12m}					ΔE_{12m}					ΔE_{12m}				
PCs	24.1	19.6	9.2	7.7	11.1	22.9	21.4	7.8	4.9	13.0	29.1	22.5	6.1	1.8	5.1
PCs+CF	39.7	32.8	18.8	14.8	18.2	37.5	27.5	12.0	9.6	15.9	47.8	33.6	16.5	13.8	13.5
PCs+LF	25.6	19.8	9.3	8.2	11.4	25.6	23.4	12.1	15.7	24.3	31.5	23.8	6.3	2.1	6.6

Table IV: R^2 of quantile regressions at different horizons for the expectation component
Columns 2-6 shows the in-sample results for the US, Columns 7-11 for DE and Columns 12-16 for the UK. Each panel represents a different horizon, with the top one showing results 3 months ahead, the middle one six months ahead and the bottom one 12 months ahead. The dependent variable in each panel is the change in the expectation component at the relevant horizon. For each horizon, we show the R^2 of three different specifications. The first one is a quantile regression with PCs as the only independent variable, while the second and third ones show results for regression in which we add either the CF or the LF on top of the PCs.

	US					DE					UK				
	$\Delta E_{3m,OOS}$					$\Delta E_{3m,OOS}$					$\Delta E_{3m,OOS}$				
Quantile	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
PCs	-16.0	-8.1	-4.5	-4.2	-9.4	-10.1	0.1	-5.9	4.2	-0.3	-12.2	-0.7	-6.1	-8.6	-3.7
PCs+CF	7.5	-0.7	-2.4	-8.1	-22.7	7.0	10.1	-8.5	2.7	-0.7	26.7	5.8	-8.5	-13.6	-9.4
PCs+LF	-26.1	-14.5	-10.1	-11.5	-16.4	-2.3	3.9	-4.7	2.4	-0.9	-22.2	-3.3	-9.3	-8.3	-3.1
	$\Delta E_{6m,OOS}$					$\Delta E_{6m,OOS}$					$\Delta E_{6m,OOS}$				
PCs	-32.4	-16.1	-9.7	-15.9	-22.3	-9.9	-0.1	-6.9	7.2	5.9	-32.2	0.3	-6.8	-11.9	-0.4
PCs+GF	-14.9	-2.9	-8.1	-12.5	-39.9	13.5	10.0	-3.6	2.8	4.9	5.8	5.3	-19.7	-19.1	6.8
PCs+LF	-49.3	-27.2	-20.2	-29.8	-38.1	-0.9	-2.6	-10.1	5.1	6.9	-44.1	-7.3	-12.1	-14.6	1.8
	$\Delta E_{12m,OOS}$					$\Delta E_{12m,OOS}$					$\Delta E_{12m,OOS}$				
PCs	-86.2	-34.8	-33.9	-42.2	-76.7	-13.1	-5.9	-11.5	-13.9	15.5	-41.8	-24.1	-31.9	-22.5	-10.5
PCs+GF	-72.9	-12.9	-14.3	-37.2	-67.3	4.1	4.7	-10.5	-20.1	-1.2	11.5	-5.8	-32.3	-13.6	-38.7
PCs+LF	-110.4	-46.0	-44.5	-58.3	-99.6	-1.8	-10.3	-27.7	-5.7	9.7	-46.5	-42.0	-51.3	-30.2	-10.5

Table V: Out-of-sample R^2 for the expectation component

Columns 2-6 shows the in-sample results for the US, Columns 7-11 for DE and Columns 12-16 for the UK. Each panel represents a different horizon, with the top one showing results 3 months ahead, the middle one six months ahead and the bottom one 12 months ahead. The dependent variable in each panel is the change in the expectation component at the relevant horizon. For each horizon, we show the R^2 of three different specifications. The first one is a quantile regression with PCs as the only independent variable, while the second and third ones show results for regression in which we add either the CF or the LF on top of the PCs. A negative R^2 means that the conditional forecast performs worse than the historical unconditional quantile estimate.

A Appendix

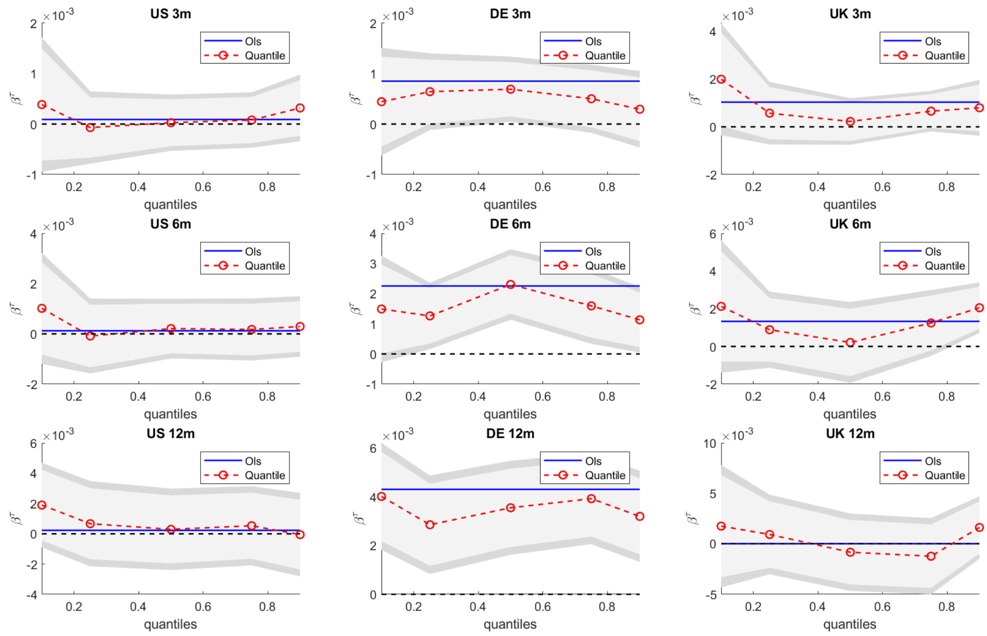

Figure 23: Beta of OLS and quantile regressions for LF - expectation component
Each Column shows OLS and quantile regression betas at different horizons for each country. The black dashed line represents the zero. The blue solid line shows the Beta from an OLS regression. The red dashed line with circles shows the β^τ obtained from quantile regressions for five different quantiles. The dependent variable of the OLS and quantile regressions are 3,6 or 12 month changes in the expectations component. The independent variables are the first three Principal Components extracted from yields (PCs) and the country-specific Local Macro Factor (LF). Grey shaded bands for the quantile regression Betas are obtained through a residual block bootstrap with an N=45 block size.

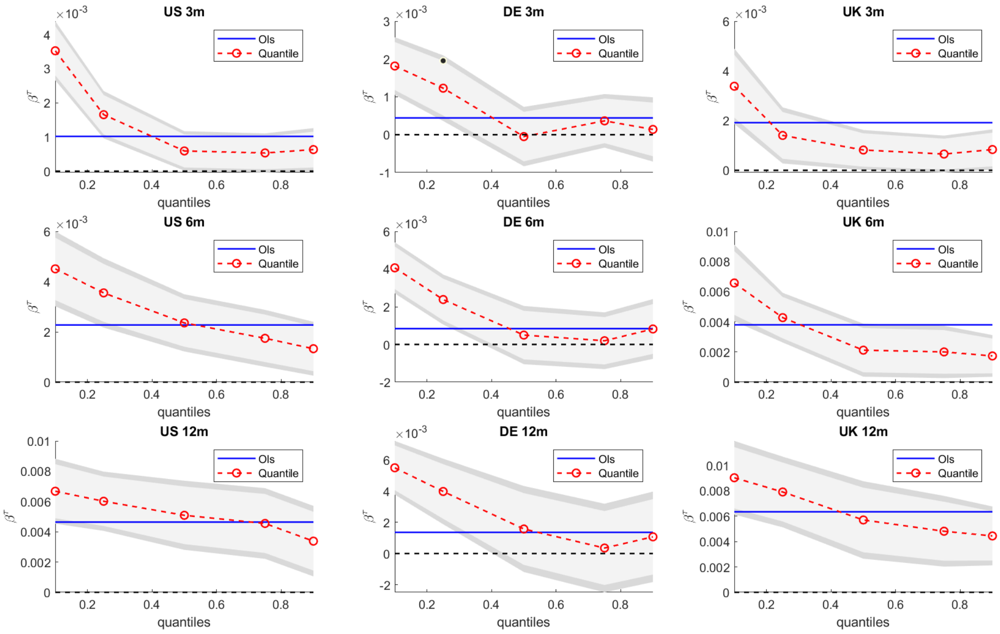

Figure 24: Beta of OLS and quantile regressions for CF - expectation component (5 PCs) Each Column shows OLS and quantile regression betas at different horizons for each country. The black dashed line represents the zero. The blue solid line shows the Beta from an OLS regression. The red dashed line with circles shows the β^τ obtained from quantile regressions for five different quantiles. The dependent variable of the OLS and quantile regressions are 3,6 or 12 month changes in the expectations component. The independent variables are the first five Principal Components extracted from yields (PCs) and the Common Macro Factor (CF). Grey shaded bands for the quantile regression Betas are obtained through a residual block bootstrap with an N=45 block size.

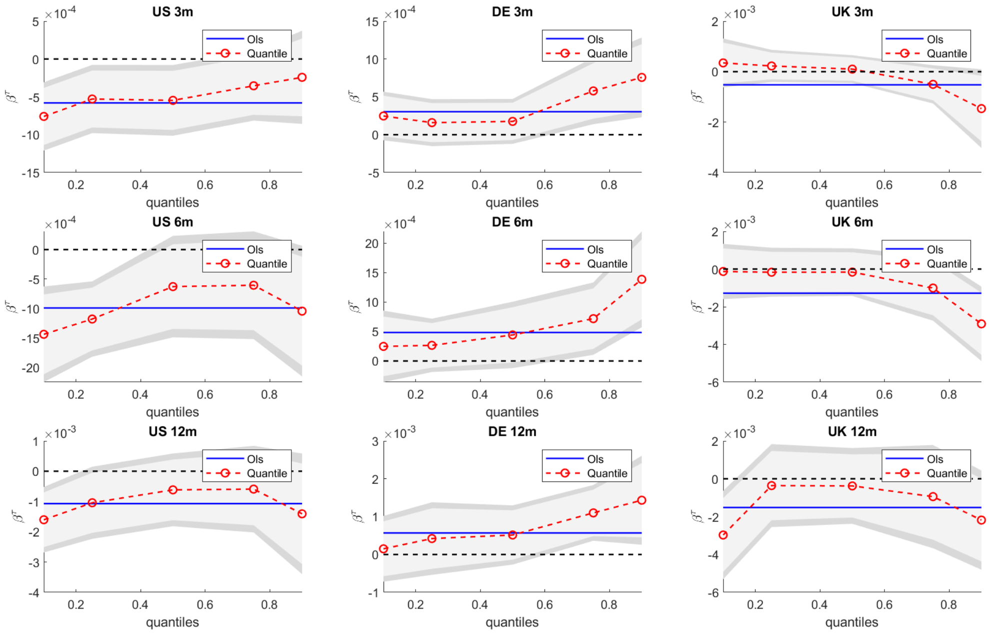

Figure 25: Beta of OLS and quantile regressions for LF - term premia component
Each Column shows OLS and quantile regression betas at different horizons for each country. The black dashed line represents the zero. The blue solid line shows the Beta from an OLS regression. The red dashed line with circles shows the β^{τ} obtained from quantile regressions for five different quantiles. The dependent variable of the OLS and quantile regressions are 3,6 or 12 month changes in the term premia component. The independent variables are the first three Principal Components extracted from yields (PCs) and the country-specific Local Macro Factor (LF). Grey shaded bands for the quantile regression Betas are obtained through a residual block bootstrap with an N=45 block size.

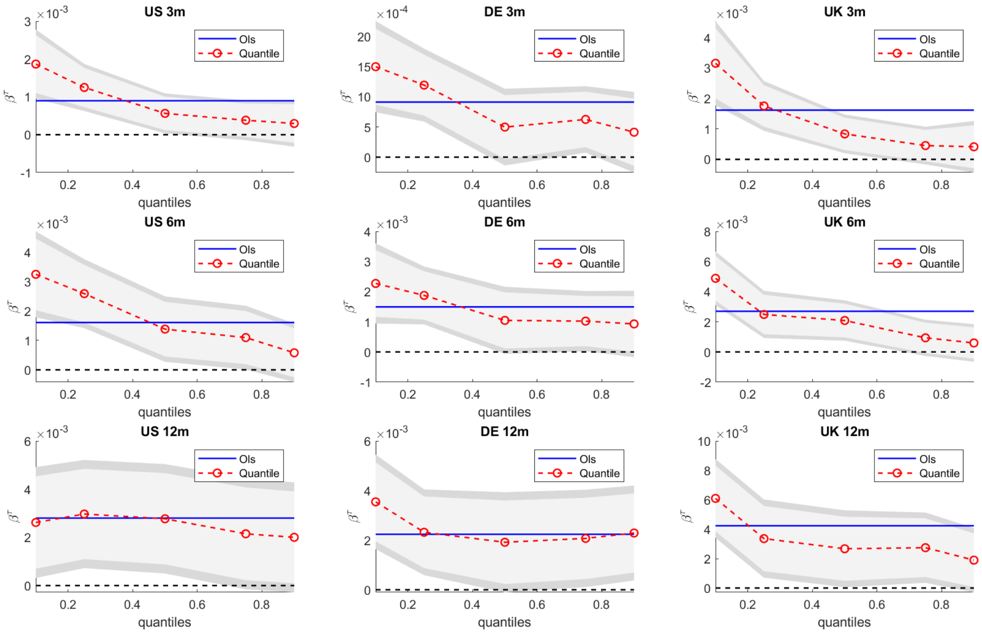

Figure 26: Expected rates and CFNAI

Each Column shows OLS and quantile regression betas at different horizons for each country. The black dashed line represents the zero. The blue solid line shows the Beta from an OLS regression. The red dashed line with circles shows the β^{τ} obtained from quantile regressions for five different quantiles. The dependent variable of the OLS and quantile regressions are 3,6 or 12 month changes in the expectations component. The independent variables are the first five Principal Components extracted from yields (PCs) and the CFNAI. Grey shaded bands for the quantile regression Betas are obtained through a residual block bootstrap with an N=45 block size.

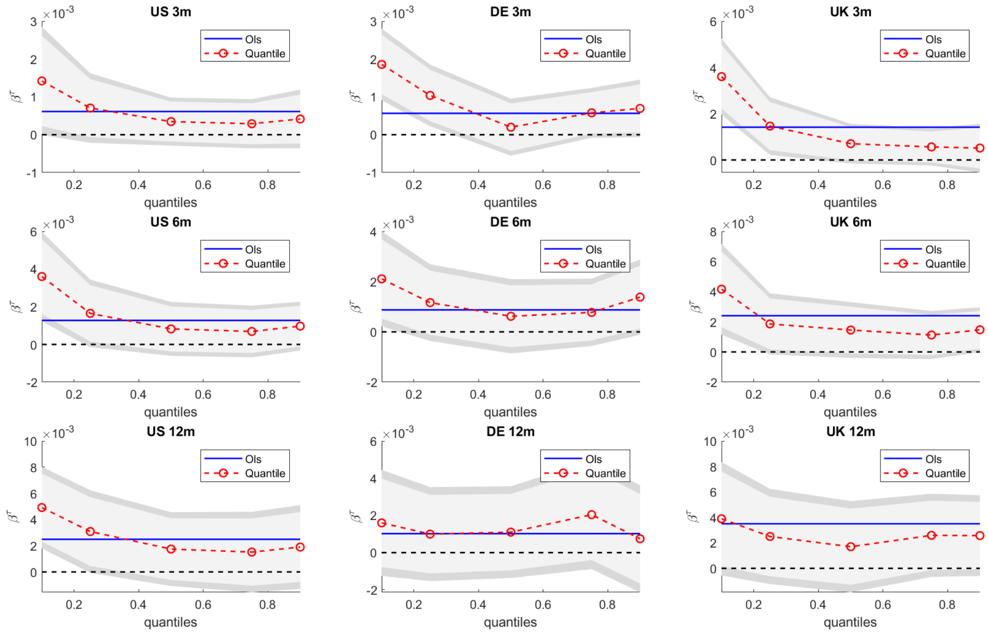

Figure 27: Expected rates and first PC of Macro Variables
Each Column shows OLS and quantile regression betas at different horizons for each country. The black dashed line represents the zero. The blue solid line shows the Beta from an OLS regression. The red dashed line with circles shows the β^τ obtained from quantile regressions for five different quantiles. The dependent variable of the OLS and quantile regressions are 3,6 or 12 month changes in the expectations component. The independent variables are the first five Principal Components extracted from yields (PCs) and first principal component extracted from all our macro variables. Grey shaded bands for the quantile regression Betas are obtained through a residual block bootstrap with an N=45 block size.

United States			
Variable	**Ticker**	**Transformation**	**Start Date**
Total Government Debt	DEBPTOTL Index	Level	Jan-90
Budget Balance/ Gdp	FDDSGDP Index	Level	Jan-90
Personal Consumption Expenditure	PCE CYOY Index	YoY	Jan-00
Consumer Price Index	CPI YOY Index	YoY	Jan-90
Consumer Price Index excl. Food & Energy	CPUPXCHG Index	YoY	Jan-90
Unemployment	USURTOT Index	$\Delta 12m$	Jan-90
Industrial Production	IP YOY Index	YoY	Jan-90
Real Private Investment	GPDITOC% Index	YoY	Mar-90
Change in Inventories	RGCDCIPI Index	Level	Mar-99
Change in NonFarm Payroll	NFP TCH Index	Level	Jan-90
Avg. Hourly Earnings	USHEYOY Index	Level	Jan-90
Factory Orders	TMNOCHNG Index	MoM	Jan-90
ISM Manufacturing Index	NAPMPMI Index	Level	Jan-90
Chicago Fed National Activity Index	CFNAI Index	Level	Jan-90
Housing Starts	NHSPSTOT Index	Level	Jan-90
New Home Sales	NHSLTOT Index	Level	Jan-90
Retail Sales	RSTAMOM Index	Level	Feb-92
Consumer Confidence Index	CONSSENT Index	Level	Jan-90
Consumer Credit	CICRTOT Index	Level	Jan-90
GDP survey μ and σ	Consensus Economics	Level	Jan-90
Pers. Consumpt. survey μ and σ	Consensus Economics	Level	Jan-90
Business Inv. survey μ and σ	Consensus Economics	Level	Jan-90
Corp. Profits survey μ and σ	Consensus Economics	Level	Jan-90
Ind. Prod. μ and σ	Consensus Economics	Level	Jan-90
Consumer Prices μ and σ	Consensus Economics	Level	Jan-90
Unemployment μ and σ	Consensus Economics	Level	Jan-90

Table A.1: Macroeconomic variables: United States

Second column reports the ticker for each series if downloaded from Bloomberg. Survey series contain the point forecast and the survey standard deviation. Third columns details the transformation used in case the series was not stationary when downloaded.

United Kingdom			
Variable	**Ticker**	**Transformation**	**Start Date**
Industrial Production	UKIPIYOY Index	Level	Jan-90
Manufacturing Production	UKMPIYOY Index	Level	Jan-90
Intermediate goods	UKIPINTM Index	Level	Jan-90
Durable consumer goods	UKIPDURM Index	Level	Jan-90
Nondurable consumer goods	UKIPNDUM Index	Level	Jan-90
Capital goods	UKIPINVM Index	Level	Jan-90
Energy	UKIPK2AJ Index	Level	Jan-97
Capacity Utilization	EUUCUK Index	Δ12M	Jan-90
Corporate Bankruptcies	UKINTOTL Index	YoY	Feb-93
Index of Services	UKISCT3M Index	Level	Dec-96
Motor Vehicle Sales	UKVHRYY Index	Level	Jan-91
Household Savings	UKSVRATI Index	YoY	Jan-90
Building Starts	UKHSEALL Index	YoY	Jan-90
House Prices	UKNBANYY Index	Level	Dec-91
Non-Residential Buildings Sales	UKPHNRSA Index	Δ12M	Mar-05
Unemployment Rate	UKUEILOR Index	YoY	Jan-90
Jobless Claims Monthly Change	UKUEMOM Index	Level	Jan-90
Unemployment Claims	UKUEMOM Index	Level	Jan-90
Hours Worked	UKLBYBUS Index	YoY	Dec-99
Weekly Wages	UKAWYWHO Index	Level	Jan-96
Real Retail Sales	UKRVINFM Index	Level	Jan-90
Retail sales of household goods	UKRVNFHM Index	Level	Jan-90
Private Consumption	UKGEABRQ Index	Level	Jan-90
EC UK Industrial Sentiment Index	EUICUK Index	Level	Jan-90
EC UK Economic Sentiment Indicator	EUESUK Index	Level	Jan-90
Consumer Confidence Index	UKCCI Index	Δ12M	Mar-93
Govt Spending	UKGENMYQ Index	Level	Jan-90
Consumer Credit	UKMSB3PS Index	YoY	Jan-90
Real Disposable Personal Income	DDIRGB Index	YoY	Jan-90
GDP survey μ and σ	Consensus Economics	Level	Jan-90
Pers. Consumpt. survey μ and σ	Consensus Economics	Level	Jan-90
Business Inv. survey μ and σ	Consensus Economics	Level	Jan-90
Corp. Profits survey μ and σ	Consensus Economics	Level	Jan-90
Ind. Prod. μ and σ	Consensus Economics	Level	Jan-90
Consumer Prices μ and σ	Consensus Economics	Level	Jan-90
Unemployment μ and σ	Consensus Economics	Level	Jan-90

Table A.2: Macroeconomic variables: United Kingdom

Second column reports the ticker for each series if downloaded from Bloomberg. Survey series contain the point forecast and the survey standard deviation. Third columns details the transformation used in case the series was not stationary when downloaded.

Germany			
Variable	**Ticker**	**Transformation**	**Start Date**
Industrial Production	GEINYY Index	Level	Jan-92
Industrial Orders	GRIORTMM Index	Level	Jan-90
Durable consumer goods	GRMPFDM Index	Level	Jan-90
Nondurable consumer goods	GRMPNDM Index	Level	Feb-91
Intermediate Goods	GRMPRAWM Index	Level	Jan-90
Capital goods	GRMPCAPM Index	Level	Jan-90
Energy	GRIPNRGM Index	Level	Feb-91
Capacity Utilization	EUUCDE Index	Level	Jan-90
New Car Registrations	GRVHREGY Index	Level	Jan-90
Residential Construction Orders	GRCOPRBY Index	Level	Jan-92
Real House Prices	DRHPDE Index	YoY	Jan-90
Building Permits	GRBPBLDM Index	Level	Jan-03
Unemployment Rate	GRUEPR Index	YoY	Jan-91
Unemployment Claims	GRUECHNG Index	Level	Feb-91
Job Vacancies	GRUFPVAC Index	$\Delta 12M$	Jan-91
Labor Productivity	GRLBGDPQ Index	Level	Jun-91
Hours Worked durable consumer goods	ETCMGCDM Index	Level	Jan-05
Hours Worked nondurable consumer goods	ETCMGNMH Index	Level	Mar-92
Real Unit Labor Costs	GRLBUCRY Index	Level	Mar-92
Retail sales (yoy naa)	GRFRINYY Index	Level	Jan-90
Wholesale Sales	GRWSRYOY Index	Level	Jan-95
Motor Vehicle Sales	GRVHREG Index	Level	Jan-90
Real Disposable Personal Income	DDIRDE Index	YoY	Jan-90
Household savings	GRHISAVR Index	$\Delta 12M$	Mar-91
ZEW Survey	GRZEWI Index	Level	Dec-91
ZEW Current Situation	GRZECURR Index	Level	Dec-91
Govt Consumption	GRGDGCQ Index	Level	Jun-91
Real Domestic Demand	GRGDDDQQ Index	Level	Jun-91
ICON Consumer Confidence Index	GRCCI Index	Level	Jan-90
GDP survey μ and σ	Consensus Economics	Level	Jan-90
Pers. Consumpt. survey μ and σ	Consensus Economics	Level	Jan-90
Business Inv. survey μ and σ	Consensus Economics	Level	Jan-90
Ind. Prod. μ and σ	Consensus Economics	Level	Jan-90
Consumer Prices μ and σ	Consensus Economics	Level	Jan-90
Unemployment μ and σ	Consensus Economics	Level	Jan-90

Table A.3: Macroeconomic variables: Germany

Second column reports the ticker for each series if downloaded from Bloomberg. Survey series contain the point forecast and the survey standard deviation. Third columns details the transformation used in case the series was not stationary when downloaded.

	US					DE					UK				
	ΔTP_{3m}					ΔTP_{3m}					ΔTP_{3m}				
Quantile	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
PCs	12.3	7.9	2.7	5.0	6.1	23.0	9.1	2.3	3.7	13.9	15.2	5.9	1.1	3.1	6.0
PCs+CF	12.9	7.9	2.7	5.5	6.5	24.3	9.7	4.1	5.0	14.5	19.3	9.0	4.6	7.4	11.6
PCs+LF	18.5	10.8	4.0	5.4	7.0	23.6	10.6	2.9	7.5	22.7	15.3	6.0	1.4	5.7	9.9
	ΔTP_{6m}					ΔTP_{6m}					ΔTP_{6m}				
PCs	13.2	10.9	6.8	5.3	5.5	22.8	12.4	3.6	6.6	17.0	21.0	9.8	3.3	4.1	9.0
PCs+CF	13.3	11.0	6.8	6.0	6.7	24.2	14.6	6.2	8.3	17.1	28.0	15.2	10.1	10.8	16.2
PCs+LF	23.1	15.7	7.8	6.2	7.4	22.8	13.7	5.4	12.2	24.7	21.9	10.1	4.1	7.0	18.3
	ΔTP_{12m}					ΔTP_{12m}					ΔTP_{12m}				
PCs	15.7	11.9	9.9	12.5	11.0	33.0	17.0	9.9	16.0	27.4	20.9	12.1	6.5	13.5	19.4
PCs+CF	15.7	12.5	10.6	12.9	11.0	33.7	18.3	12.2	18.2	29.9	34.7	19.6	15.1	21.8	27.7
PCs+LF	25.9	14.4	10.6	12.6	11.2	33.0	17.0	11.4	18.8	30.6	28.2	13.0	7.9	15.2	26.0

Table A.4: R^2 of quantile regressions at different horizons for the term-premia component Columns 2-6 shows the in-sample results for the US, Columns 7-11 for DE and Columns 12-16 for the UK. Each panel represents a different horizon, with the top one showing results 3 months ahead, the middle one six months ahead and the bottom one 12 months ahead. The dependent variable in each panel is the change in the term premia component at the relevant horizon. For each horizon, we show the R^2 of three different specifications. The first one is a quantile regression with PCs as the only independent variable, while the second and third ones show results for regression in which we add either the CF or the LF on top of the PCs.

	US					DE					UK				
	ΔTP_{3m}					ΔTP_{3m}					ΔTP_{3m}				
Quantile	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
PCs	-13.2	-9.2	-19.2	-15.7	-22.5	10.8	-3.3	-4.3	-12.0	-4.5	1.5	-7.5	-8.6	-7.9	-15.9
PCs+GF	-10.5	-11.6	-21.1	-20.3	-28.6	9.9	-9.9	-9.1	-20.6	-16.3	-7.2	-10.9	-3.2	-1.7	-13.9
PCs+LF	-5.7	-10.0	-18.3	-17.5	-23.2	16.5	2.7	-7.3	-27.2	-11.0	-2.3	-10.1	-10.7	-9.7	-17.5
	ΔTP_{6m}					ΔTP_{6m}					ΔTP_{6m}				
PCs	-30.7	-27.5	-36.9	-34.6	-30.9	1.7	-5.1	-14.9	-25.2	-26.0	-4.6	-14.0	-8.9	-12.0	-33.8
PCs+CF	-36.2	-29.1	-36.4	-36.2	-37.6	-4.6	-11.2	-28.4	-47.6	-48.8	-13.1	-16.1	-13.6	-24.3	-14.9
PCs+LF	-31.3	-27.2	-37.4	-31.0	-34.6	3.0	5.7	-14.8	-38.7	-48.5	-8.5	-21.3	-19.3	-18.0	-46.7
	ΔTP_{12m}					ΔTP_{12m}					ΔTP_{12m}				
PCs	-109.7	-71.0	-67.5	-66.2	-41.2	23.5	-7.9	-40.8	-55.1	-31.1	-13.1	-20.4	-33.4	-19.6	-12.7
PCs+CF	-98.2	-63.6	-72.0	-67.6	-41.4	14.6	-15.4	-73.5	-88.6	-60.0	-37.9	-37.1	-34.6	-38.1	-16.2
PCs+LF	-118.1	-73.6	-66.7	-69.6	-49.4	23.1	-15.4	-39.9	-62.0	-40.8	-19.6	-41.0	-50.3	-39.9	-15.4

Table A.5: Out-of-sample R^2 for the term premia component

Columns 2-6 shows the in-sample results for the US, Columns 7-11 for DE and Columns 12-16 for the UK. Each panel represents a different horizon, with the top one showing results 3 months ahead, the middle one six months ahead and the bottom one 12 months ahead. The dependent variable in each panel is the change in theterm premia at the relevant horizon. For each horizon, we show the R^2 of three different specifications. The first one is a quantile regression with PCs as the only independent variable, while the second and third ones show results for regression in which we add either the CF or the LF on top of the PCs. A negative R^2 means that the conditional forecast performs worse than the historical unconditional quantile estimate.