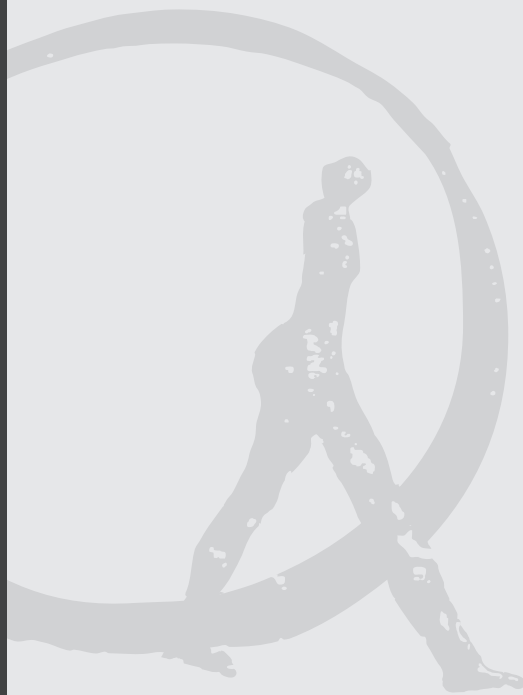


Predicting Risk Premia for Treasury Bonds: The ERI Risk Premium Monitor

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EDHEC pursues an active research policy in the field of finance. EDHEC-Risk Institute carries out numerous research programmes in the areas of asset allocation and risk management in both the traditional and alternative investment universes.

1. Why Risk Premia Matter

Investors in the Treasury market often observe an upward-sloping yield curve.¹ This means that, by assuming 'duration risk', they can very often invest at a higher yield than their funding cost. Yet, if the Expectation Hypothesis held true – if, that is, the steepness of the yield curve purely reflected expectations of future rising rates – no money could on average be made from this strategy. This prompts the obvious question: *When* does the steepness of the yield curve simply reflect expectations of rising rates, and *when* does it embed a substantial risk premium?

More generally, one can decompose any observed market yield into an expectation, a risk-premium, and a convexity component. The investment relevance of being able to carry out this decomposition is clear. Take, for instance, a bond manager whose performance is assessed against a Treasury benchmark. Apart from tactical decisions, her main strategic investment choices boil down to deciding whether to be long or short duration with respect to the benchmark. Knowing whether she is handsomely or poorly compensated for taking this duration risk – ie, whether the embedded risk premium is positive or negative, and, if positive, whether it is large or small – is key to her long-term performance. Or take a multi-asset portfolio manager. Deciding the relative portfolio weights among the different asset classes (or, more correctly, among the different risk factors), depends in great part on the time-varying degree of compensation attaching to these different factors.

In all these cases, and in many more, being able to estimate in a reliable and robust manner the risk premium currently attaching to yields, and hence the expected excess returns, is key to successful strategic investment decisions. It is for this reason that EDHEC-Risk Institute is launching the ERI Risk Premium Monitor: a robust tool to extract from market and monetary-policy information a state-of-the-art estimate of the risk premium. The rest of this note explains how this task is achieved, and the theoretical underpinnings of the analytical tools used for the task.

2. Predicting Excess Returns

What explains (and predicts) excess returns in default-free Treasury bonds? And how much can one explain?

Until recently, the answers to both questions used to be simple and short: 'the slope', and 'rather little', respectively. State of the world characterised by a steep upward-sloping yield curve used to be considered indicators of positive expected excess returns. The degree of predictability was however modest (with R^2 of the regression of the predicted and realised excess returns never exceeding 20%). This regularity used to be explained along the following lines. Consider first the empirical observation that the Sharpe Ratios from investing in long-dated Treasuries by funding with short-dated Bills show very strong and very clear business-cycle dependence. See Tab (1).

Looking at this table, one observes that the recessionary periods are associated with the monetary authorities cutting rates and therefore engineering an upward-sloping yield curve. Note how the Sharpe ratios are very negative when the curve tends to be flat to inverted (during the tightening cycles), and very positive during recessions (when the curve tends to be steeply upward sloping). It is natural to assume that in the troubled recession periods investors should become more risk averse. It is therefore plausible to deduce that the magnitude of the risk compensation should be linked to this business-cycle variation of risk appetite. This standard explanation for the business-cycle component of the excess return predictability coming from the slope is well-rehearsed (see, eg, Fama (1986), Stambaugh (1988), Fama and French (1989), Dahlquist and Hasseltoft (2016)). In essence it points to the fact that, since the steepness of the yield curve (the 'level of the slope')

1 - Since 1971, the yield curve has been upward sloping (with the 10-year yield above the 1-year yield) for almost 84% of the time. Unless investors repeatedly and erroneously expected rates to rise almost all of the time, this is prima facie evidence of the existence of a risk premium.

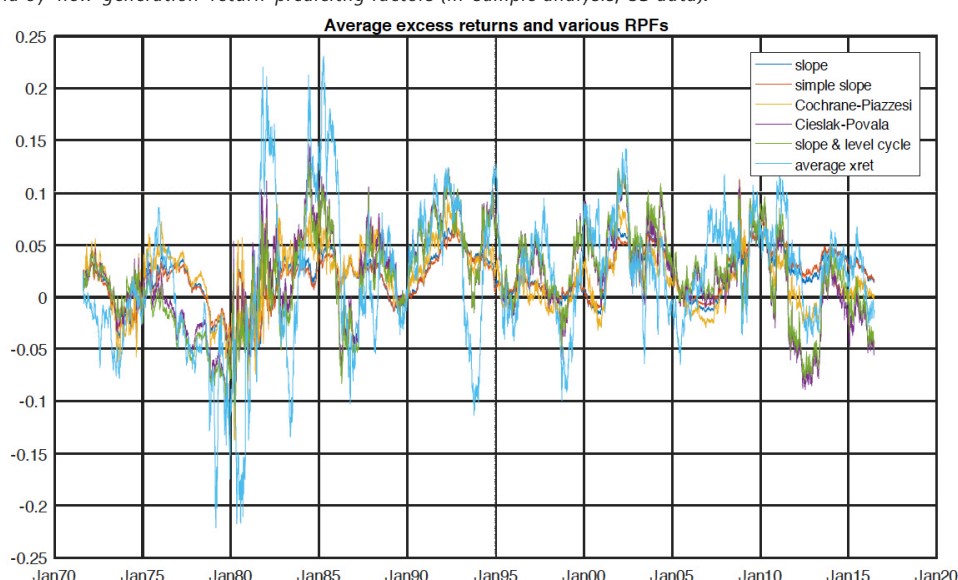
has well-known business-cycle properties, risk aversion (and hence premia) is likely to be higher in periods of economic distress – and to display the same business-cycle periodicity.

Tab 1: Sharpe ratios for the excess return 'carry' strategy applied to US Treasuries during the 1955-2014 period, subdivided i) into different chronological sub-periods, ii) into periods of recessions or expansions, and iii) during tightening cycles. Data adapted from Naik et al (2016).

	2-year	5-year	10-year
Full Sample	0.20	0.20	0.16
1955-1986	0.04	-0.01	-0.07
1987-2014	0.59	0.56	0.49
Recession	0.82	0.72	0.59
Expansion	0.01	0.06	0.05
1st half Expansion	0.52	0.50	0.45
2nd half Expansion	-0.61	-0.50	-0.48
Tightening Cycles			
1979:Q3-1981:Q2	-1.06	-1.13	-1.23
1993:Q3-1995:Q1	-0.79	-0.86	-0.86
2004:Q2-2006:Q2	-1.52	-0.90	-0.50

(1)

Figure 1: Average excess returns from the invest-long/fund-short strategy described in detail in the text, and the excess returns predicted by the slope and by 'new-generation' return-predicting factors (in-sample analysis, US data).



Starting from the mid-2000s, several results have questioned this received wisdom²: these more recent investigations suggest that different return-predicting factors may be far more complex than the simple slope; and their (in-sample) predictions of excess returns sometimes produce surprisingly high R^2 – surprisingly high, that is, by the modest standards of excess return studies. Why is this the case? And what is the economic significance of the new, more complex, factors?

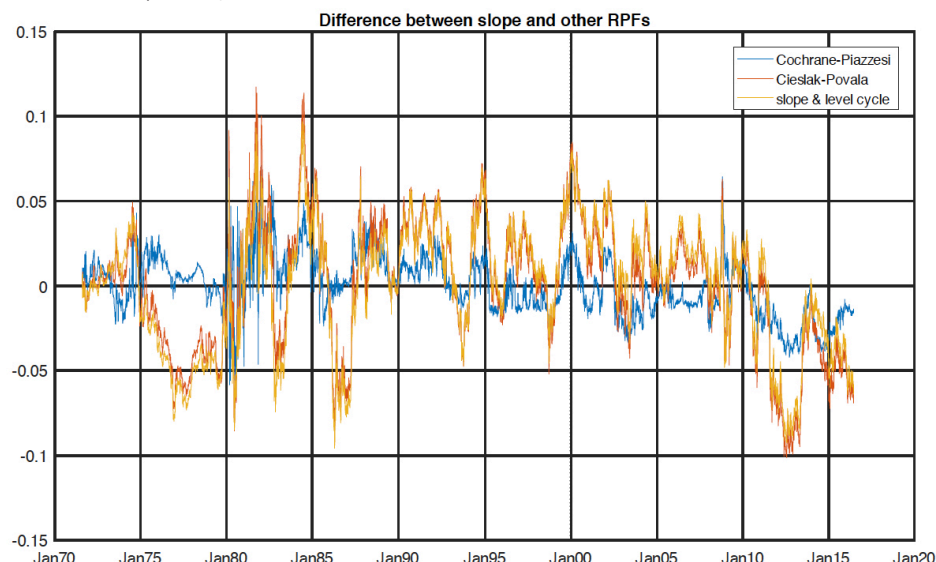
The motivation of the question can be readily understood by looking at Figures (1) and (2), which focuses on the *predictions* made by the old- and new-generation factors, rather than on the shape of the factors themselves.

More precisely, Figure (1) shows the average excess returns from the invest-long/fund-short strategy described in detail in what follows, and the excess returns predicted by the slope and other 'new-generation' return-predicting factors. As one can readily appreciate, these predictions are all strongly correlated, and the new-generation ones particularly so. All the return-predicting factors tell roughly the same story, but it is clear even from a causal inspection that the new-generation factors add a substantial twist to the slope story.

2 - Some reference papers for the new wave of excess-return studies are Cochrane and Piazzesi (2005), Cieslak and Povala (2010a, b), Hellerstein(2011), Rebonato (2015), Dai, Singleton and Yang, (2004), Cochrane (2015).

Figure (2) makes this intuition clearer by showing the differences between the prediction produced by the slope, and the predictions produced by the new-generation factors (in-sample analysis). It is important to note that what is added on top of the slope predictions is rather similar (and sometimes an extremely similar), despite the fact that these return-predicting factors are constructed following *prima facie* extremely different strategies.

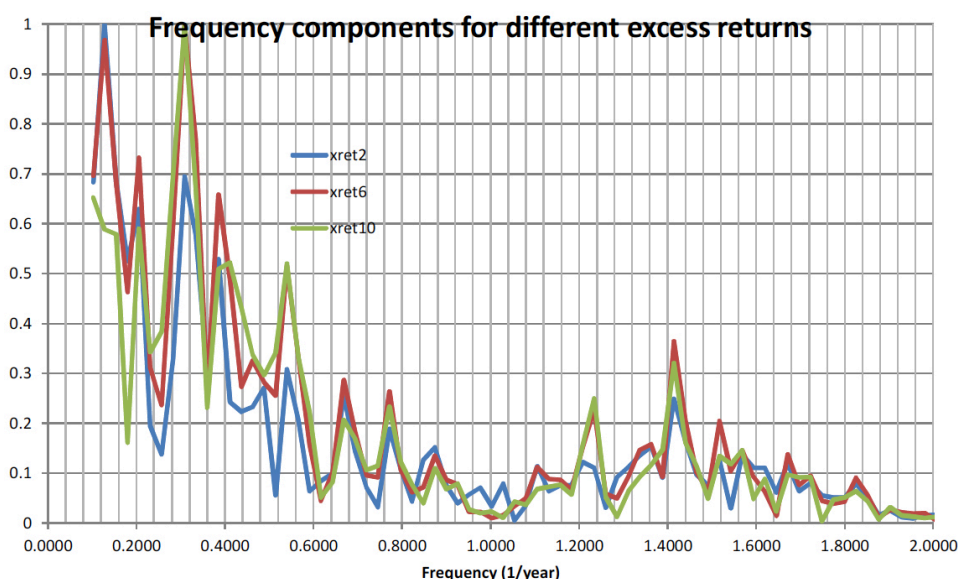
Figure 2: The differences between the prediction of average excess returns produced by the slope, and the predictions produced by the new-generation factors (in-sample analysis, US data.)



This qualitative analysis prompts the following questions:

1. Are these 'extra predictions' (which are of the same order of magnitude as the average excess return themselves) informative, or, as Bauer and Hamilton (2015) argue, are they just a result of over-fitting?
2. Why do such apparently different return-predicting factors produce such similar incremental predictions (with respect to the slope predictions)?
3. What is the financial and economic interpretation of these common differences in prediction (again, with respect to the slope predictions)?

Figure 3: Normalised frequency components of the power spectrum for the 2-, 6- and 9-year returns. Frequencies in years⁻¹.



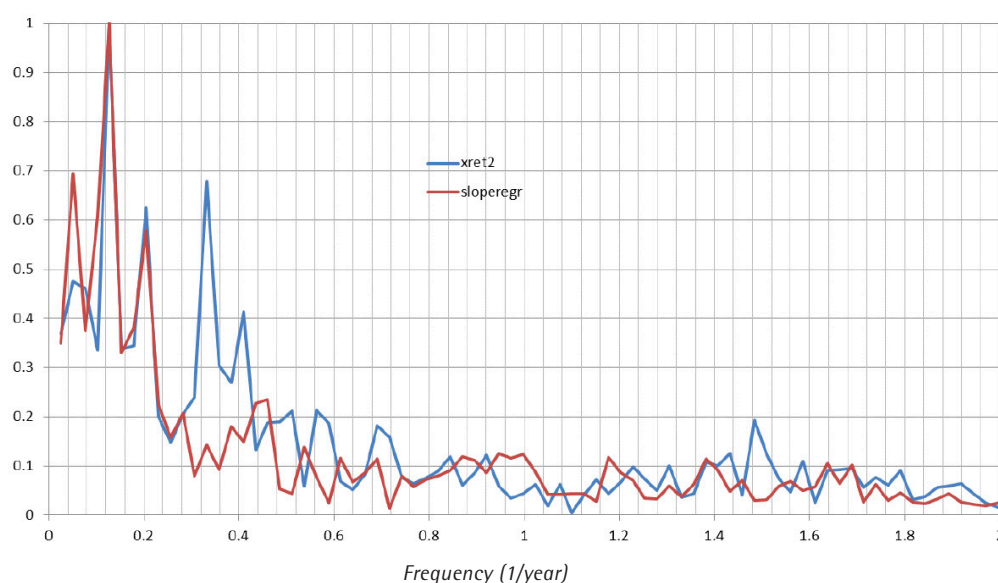
A full answer would take too long a detour (see, eg, Rebonato (2018)). We can however summarise the main findings by pointing to two important elements of the excess returns and factor time series.

The first insight is linked to the frequency decomposition of excess returns. As we discuss at greater length below, the power spectrum of excess return certainly shows the low-frequency (business-cycle-period) that can be captured by the 'old' slope factors. There is an important fraction of the return predictability, however, that has a much higher frequency signature, and that requires higher principal components to be captured. It is (in part) because of its ability to capture these high-frequency components that a factor such as the Cochrane-Piazzesi (which makes use of high-order, and high-frequency, principal components) fares better than the slope by itself.

The second insight suggests that a large fraction of return predictability comes from detecting the cyclical straying of yields from a long-term fundamental trend. Once an effective decomposition of the yield dynamics into trend and cycle is carried out, one finds that the different degrees of mean reversion of the various return-predicting factors explain very well the different degrees of excess returns predictability.

Let us look more carefully at these two insights one at a time. These first one can be formalised by a Fourier decomposition of excess returns on the one hand, and return-predicting factors on the other. Looking at Figure (3) one observes for all investment horizons important contributions from both low-frequency ('business-cycle' periodicity), and higher frequencies, with periodicities well under one year.

Figure 4: Frequency power spectrum of the 2-year excess returns and of the slope return-predicting factor.

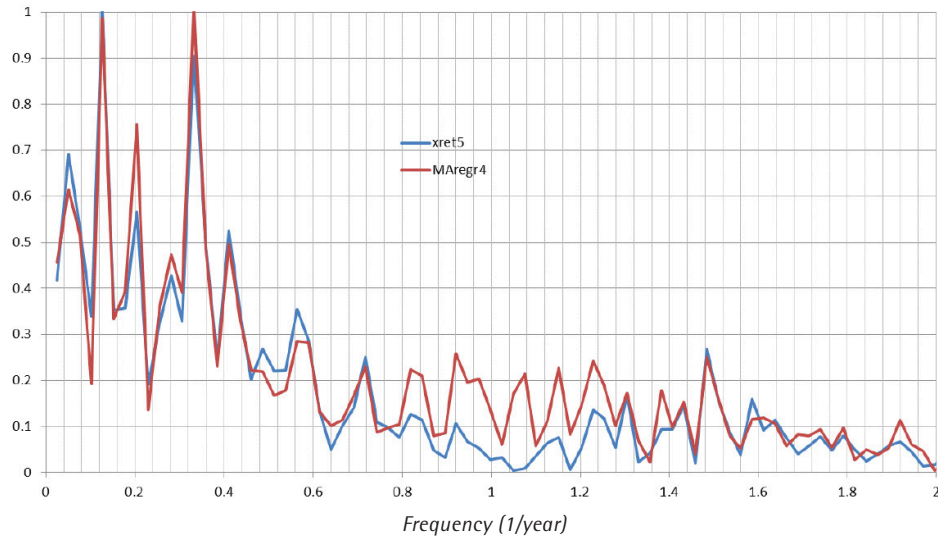


When we compare these results with the similar frequency decomposition for the candidate return-predicting factors, we find that they naturally fall into two broad classes: low-frequency and high-frequency ones. These two classes factors 'pick up' different portions of the excess return spectrum. See, for instance, Figures (4) and (5). The first figure superimposes the normalised frequency spectrum of the slope and of the 2-year excess return. Note how the slope recovers the low frequency peaks of the excess returns, but completely misses the medium- and high-frequency components. As a contrast, the second figure (Figure (5)) shows the remarkable match in frequencies between the power spectrum of the 5-year excess returns and the spectrum associated with a factor built using one of the detrending techniques described in what follows.

Why do both of these two different 'types of' factors help the prediction of excess returns?

We propose that two distinct financial mechanisms can explain the predictability of excess return: the first, ie, the one associated with low frequency changes in excess returns, is linked with changes in risk aversion with business-cycle periodicity. As we have seen, the low-frequency, slope-related component of return predictability can be traced back to a state-dependent variation in risk appetite. As for the second financial mechanism, associated with higher-frequency cycles, we suggest that it comes from the actions of pseudo-arbitrageurs who bring back in line with fundamentals the level and slope of the yield curve. These deviations have a much quicker mean-reversion, and are therefore associated with the higher-frequency components of the excess return spectrum. In agreement with what Cochrane and Piazzesi (2005) and Adrian Crump and Moench find, these distortions of the yield curve require relatively high principal components to be captured.

Figure 5: Frequency power spectrum of the 5-year excess returns and of the return-predicting factor built using the slope and the cycle to the 4-year moving average of the level of yields.



As mentioned, the second essential ingredient of the 'additional' (cycle-like) return-predicting factors is that they should be quickly mean-reverting. The explanation here is that when yields move away from fundamentals, they revert to their 'correct' levels much faster than over a business cycle. An effective return-predicting factor must capture this feature. This intuition can be formalised as follows. We can express the level and slope of the yield curve as a sum of (differently estimated) cyclical and trend parts:

$$lv_t = lv_t^{cyc, \bullet} + lv_t^{trend, \bullet} \quad (2)$$

$$sl_t = sl_t^{cyc, \bullet} + sl_t^{trend, \bullet}, \quad (3)$$

where the symbol ' \bullet ' is a placeholder for 'the type of decomposition'.

Next, we carry out regressions of the average excess returns against the various cycles and trends. Simplifying greatly, we can draw the remarkable conclusion that for all the currencies we look at, and for all the de-trending procedures we use, the excess return explanatory power of the level cycle is correlated with the strength of mean reversion of the level cycle. More precisely, first we establish the strength of the mean-reverting behaviour of the variously-estimated cycles:

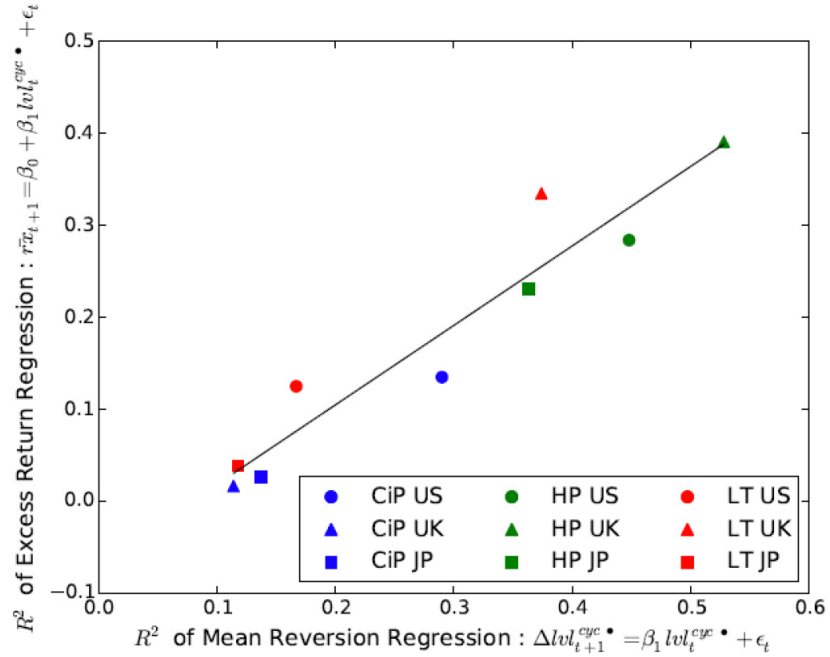
$$\Delta lv_{t+1}^{cyc, \bullet} = -\kappa^{lv, \bullet} lv_t^{cyc, \bullet} + \epsilon_{t+1} \quad (4)$$

with

$$\Delta l v l_{t+1}^{cyc, \bullet} = l v l_{t+1}^{cyc, \bullet} - l v l_t^{cyc, \bullet} \quad (5)$$

and the symbol, ' \bullet ', as above, is a placeholder for CiP, HP or LT.

Figure 6: Scatter plot whose x-axis is the R^2 of the mean-reversion regression of the level cycle and y-axis is the R^2 of excess return regression in Equation (4)

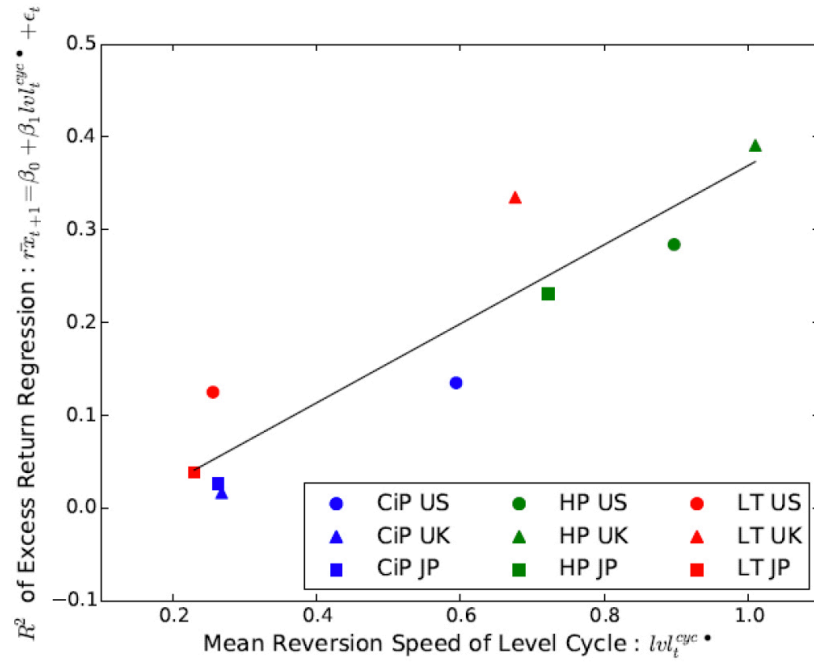


When we do so, we find that the strength of the mean reversion (the magnitude of the mean-reversion speed) explains very well the excess return explanatory power of the various cycles: the prediction of excess returns (measured by the R^2) is high when the mean reversion of the level cycle is strong. This is shown in Figures (6) and (7): Figure (6) shows a scatter plot whose x-axis is the R^2 of the mean-reversion regression of the level cycle and y-axis is the R^2 of excess return regression in Equation (4); and Figure (7) shows a scatter plot whose x-axis is the reversion speed of the level cycle and y-axis is the R^2 of excess return regression in Equation (4).

In short: when we look at in-sample data, the more a detrending technique produces a strongly-mean reverting level cycle, the better the cycle itself predicts excess returns.

This source of predictability linked to fast mean reversion also explains the shape of the Cochrane 'tent', and of many of the more exotic patterns found in the recent literature for the return-predicting factors, (such as Rebonato's 'bat', or the complex patterns found by Dai, Singleton and Yang (2004) and Villegas (2005)). Indeed, the common feature of all these return-predicting factors is that they are all made up of highly-correlated regressors (yields or forward rate) with *opposite-sign loadings*. So, in essence, all these return-predicting factors are all complex differences of yields. When we create time series of cross-sectional differences of yields, we find that they are strongly mean-reverting, with half-lives ranging between 1 and 2.5 years, and with power spectra with significant frequency contributions in the high-frequency spectrum of excess returns. When we look at the time series of excess returns, we find similarly strong mean-reverting properties, and very similar reversion speeds, with half-lives ranging from 0.85 to 1.5. So, we propose that the tent-family return-predicting factors are effective because they construct weighted differences of yields or forward rates that happen to display the required periodicity.

Figure 7: Scatter plot whose x-axis is the reversion speed of the level cycle and y-axis is the R^2 of excess return regression in Equation (4)



The full picture is more complex, but, simplifying greatly, we can say that powerful return-predicting factors can be extracted when it is possible to separate effectively a long-term trend for the level of rates, and when the residuals are strongly mean-reverting. The more effective the decomposition, and the stronger the speed of mean-reversion, the more significant the coefficients in the predictive regressions of excess returns, and the higher the R^2 statistics. These results are robust with respect to different choices of (in-sample) de-trending technique.

Apart from their intrinsic interest, taken together these two insights about the frequency components of excess returns and about their mean reverting properties give us a very effective procedure to construct powerful and very parsimonious return-predicting factors: in order to predict excess returns we need a frequency match (both for the long and in the short periods), and a speed-of-mean-reversion match. When these two conditions are satisfied, a number of similarly (and highly) effective and robust factors can be built almost by inspection. The new factors are parsimonious (they only require one slope-like component and one cycle-like component), intuitively understandable (thanks to the financial interpretation offered above) and highly effective (both in-sample and out-of-sample they predict as well as, and often better than, the Cochrane-Piazzesi or the Cieslak Povala Factors).

3. Regularising the Statistical Information

Interesting as these results are, all predictions about risk premia gleaned from purely statistical studies suffer from two main shortcomings:

1. there is no guarantee that the risk premia thus estimated will be consistent with the absence of arbitrage;
2. no use is made of any information about the level of market yields: clearly, an estimate of, say, a -3% term premium has a different degree of *ex ante* plausibility depending on whether the corresponding market yield is, say, at 6% or 2% .

Traditionally, the 'other' route to estimating risk premia has been via the use of arbitrage-free affine term-structure models. Unfortunately, affine models do incorporate information about the level of market yields, and do ensure absence of arbitrage, but rarely do they have the flexibility

to capture the rich information conveyed by the statistical analysis³. Both approaches are useful, but neither tells the whole truth.

The ERI Risk premium Monitor exploits the relative strengths of the two approaches and, to some extent, overcomes their weaknesses. It does so by complementing the predictions from the statistical estimate with the assessment of the risk premium coming from a member of the family of affine models described in Rebonato (2017). The simplest of these models uses as state variables the short rate, its own stochastic reversion level and the market price of risk. To simplify the analysis, and in line with standard findings (see, eg, Cochrane & Piazzesi (2005, 2008), Adrian, Crump & Moench (2013)), the model assumes that investors only seek compensation for the uncertainty about the level of rates, which we proxy in our approach as the long-term reversion level of the reversion level. The model then is as follows:

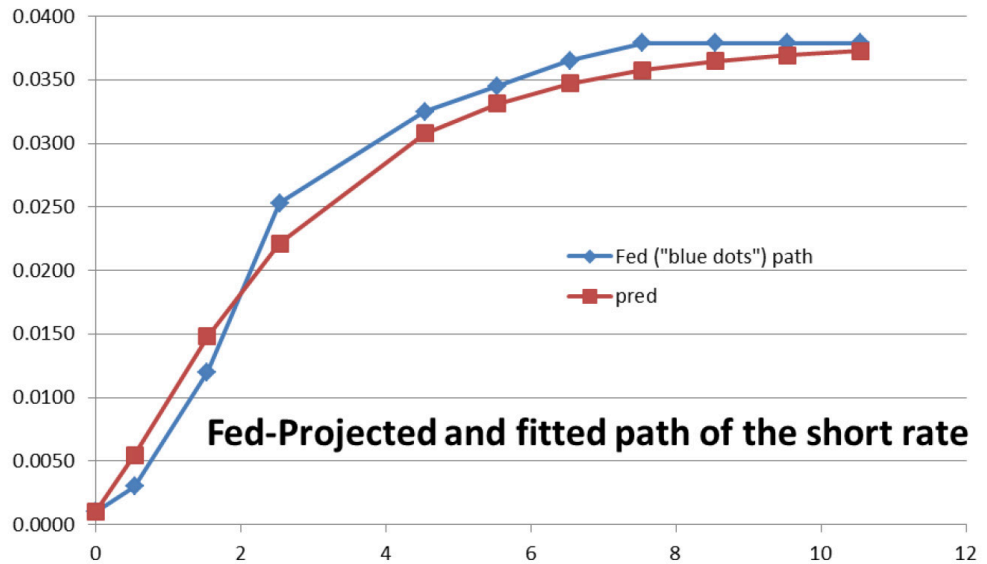
$$dr_t^Q = \kappa_r^{\mathbb{P}} [\theta_t - r_t] dt + \sigma_r dz_t^r \quad (6)$$

$$d\theta_t^Q = \kappa_\theta^P [\hat{\theta}_t^{\mathbb{P}} - \theta_t] dt + \lambda_t \sigma_\theta dt + \sigma_\theta dz_t^\theta \quad (7)$$

$$d\lambda_t = \kappa_\lambda [\hat{\lambda}_t - \lambda_t] dt + \sigma_\lambda dz_t^\lambda, \quad (8)$$

where r_t , θ_t and λ_t are the time- t value of the short rate, of its instantaneous reversion level (the 'target rate') and the market price of risk, respectively; σ_r , σ_θ , and σ_λ are the associated volatilities; $\hat{\theta}_t^{\mathbb{P}}$ and $\hat{\lambda}_t$ are the reversion levels of the 'target rate' and of the market price of risk, respectively; and the increments dz_t^r , dz_t^θ and dz_t^λ suitably correlated (see below). The model is fully specified once the initial state, r_0 , θ_0 and λ_0 is given.

Figure 8: The path traced by the Fed 'blue dots' and the most similar path for the expectation of the \mathbb{P} -measure path of the Fed funds.



The reader is referred to Rebonato (2017) for the financial motivation of the model, and for a detailed description of its performance. For our purposes, the important observation is that in this model the non-market information comes from the forward guidance about the future path of the short rate provided by the Fed. The \mathbb{P} -measure path of the Fed funds (the 'short rate') is extracted from the 'blue dots' provided quarterly by the Fed, and the \mathbb{P} -measure parameters of the model are determined so as to recover as best as possible the expected path. See Figure (8).

3 - This is usually because the affine dependence of the market price of risk on the state variables (required to retain tractability) is too stylised to be quantitatively useful.

When the two sources of information are combined, we obtain for the 10-year term premium the composite robust estimates shown in Figures (9) and (10).

As Figure (9) shows, the correlation among the statistical and the model-based estimate are above 90% for all the models. This is remarkable, considering how different the approaches and the sources of information are.

This congruence gives us confidence about the robustness and the reliability of the combined approach.

Figure 9: Estimates from the statistical models and the affine model, rescaled to have the same volatility. The correlation among all the estimate is over 90%.

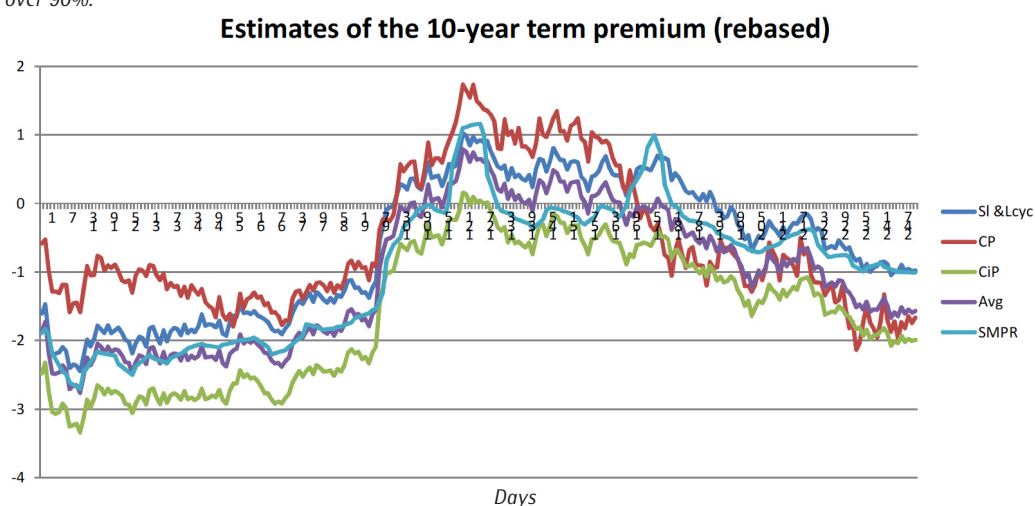
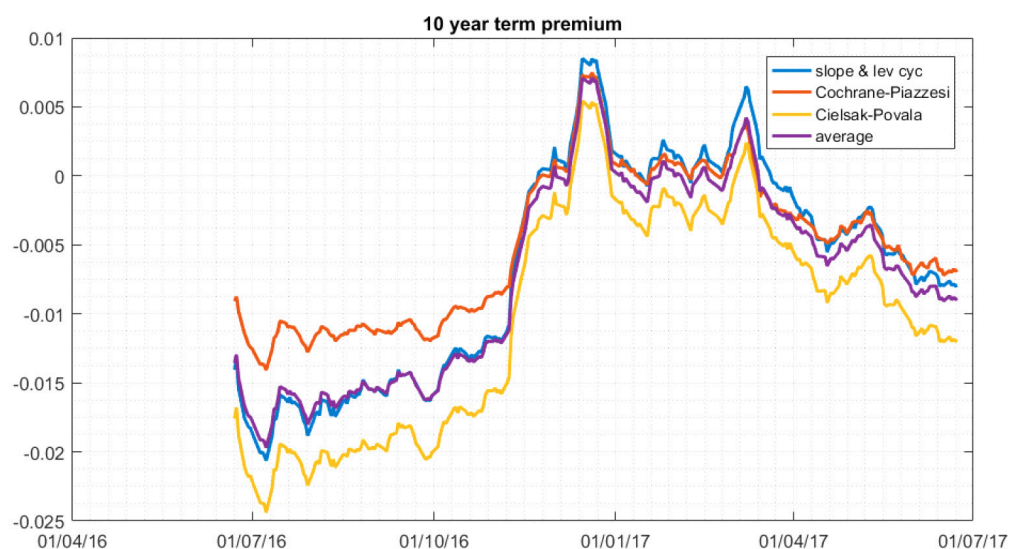


Figure 10: The result of combining the statistical estimates of the 10-year term premium from the models in the legend combined with the estimate from the affine model.



4. Conclusions

In this note we have given a glimpse of the latest and most exciting research strands carried out in the academic world in general, and at the EDHEC-Risk Institute in particular, about the robust estimation of the yield risk premia. The predictions about the term premia for various yield maturities of the US Treasuries will be regularly provided, together with more formal research papers on these and related topics. Much work remains to be done, for instance by looking at different currencies, and at related asset classes. However, we believe that the present offering can already be of real practical use and interest for practitioners and for academics.

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