Varying Risk Premia in International Bond Markets

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Abstract

Cochrane and Piazzesi (2005) use forward rates to forecast future bond returns. We extend their approach by applying their model to international bond markets. Our results indicate that the unrestricted Cochrane and Piazzesi (2005) model has a reasonable forecasting power for future bond returns. The restricted model, however, does not perform as well on an international level. Our results do not confirm the systematic tent-shape of the estimated parameters found by Cochrane and Piazzesi (2005). The forecasting models are used to implement various trading strategies. These strategies exhibit high information ratios when implemented in individual countries or on an international level. We also introduce an alternative specification to forecast future bond returns. This alternative specification delivers superior risk-adjusted returns in our trading strategy.

1. Introduction

Asset pricing is one of the largest research fields in finance. One aspect of asset pricing is the forecasting of future asset returns. While the capital asset pricing model and its various extensions link the systematic risk of assets to their expected future performance, a more challenging task is to forecast future realized returns. In the fixed income sector a range of approaches are developed to forecast future bond returns. Among others, Stambaugh (1988), Ilamen (1997), Cochrane and Piazzesi (2005), and Ludvigson and Ng (2006) analyze models for the forecasting of bond returns. However, most of this research is performed for the US market. Furthermore, no study focuses on the profitability of these models in trading strategies. This article fills this gap by studying the application of the Cochrane and Piazzesi (2005) methodology on international bond markets. Furthermore, we use the return forecasts to derive profitable trading strategies.

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Cochrane and Piazzesi (2005) use forward rates, i.e. financial data to forecast future bond returns. Forward looking financial data are thought to proxy for time varying business conditions. This is different to macroeconomic approaches which attempt to explain future bond returns on the basis of economic data that are assumed to directly represent time varying business conditions. Kim and Moon (2005) find that a single macro index consisting of inflation, real activity, and money market figures can forecast up to 37% in the variation of bond excess returns on an annual basis. An article by Ludvigson and Ng (2006) uses a large range of macroeconomic variables and tests for their ability to forecast bond excess returns. Ludvigson and Ng (2006) find that the forecasting power of these macroeconomic variables is above and in excess of the predictive power found in the forward and yield curves. Determinants of credit spread changes are analyzed by Collin-Dufresne et al. (2001). The authors find that monthly credit spread changes across different bonds are mostly driven by a single common factor. This factor cannot be explained by a range of macroeconomic and financial variables. In contrary, credit spread changes appear to be principally driven by local supply and demand shocks which are independent from credit-risk factors and liquidity proxies. Hence, the impact of macroeconomic variables on the performance of bonds cannot be extended to the changes in credit spreads.

Another strand of research deals with the forecasting of the yield curve as a whole. Since the shape of the yield curve determines bond prices, this is another route to forecast future bond returns. An article by Diebold and Li (2006) uses a variation of the yield curve model introduced by Nelson and Siegel (1987, 1988) to derive a smooth yield curve from the yields observed in the USA. Diebold and Li (2006) find that the three factors of their model correspond to the level, slope, and curvature of the yield curve. These factors appear to be mean-reverting. Their model delivers encouraging results for the forecasting of the yield curve. The Diebold and Li (2006) model is extended by Diebold et al. (2006) and applied to international fixed income markets. The conducted analyses find evidence for global yield factors which have a significant influence on national yield curves. Diebold et al. (2007) link the factors of the model by Nelson and Siegel (1987, 1988) with macroeconomic factors. They find a strong forecasting ability of macroeconomic factors for the model factors and the shape of the yield curve. Therefore, macroeconomic factors also have an impact on future bond returns. Ang and Piazzesi (2003) study VAR models for the yield curve. In a variance decomposition the authors show that macroeconomic factors can explain up to 85% of the volatility in bond yields, where the explanatory power is best at the short and middle section of the yield curve. They find that the inclusion of macroeconomic variables can improve the forecasting ability of the VAR model considerably. An analysis of the forecasting ability of affine models for future Treasury yields can be found in Duffee (2002). Hall et al. (1992) show for data from 1970 to 1988 that yields to maturity of US treasury bills are cointegrated. An error correction model is shown to provide meaningful forecasts of changes in yields.

Our article adds to the previous literature on trading strategies in fixed income instruments. An article by Chua et al. (2006) studies strategies which postulate a mean reversion in the level, slope, and curvature of the yield curve. After consideration of transaction costs, they find a good performance for trades which are based on a mean-reverting yield curve slope. Duarte et al. (2006) undertake a detailed analysis of widely-used fixed income trading strategies. The article analyzes swap spread arbitrage, yield curve arbitrage, mortgage arbitrage, volatility arbitrage, and capital structure arbitrage. The strategies which require a higher intellectual capital for the implementation provide significant alphas even after controlling for risk factors. A further fixed income trading strategy is suggested by Ilmanen (1997). He identifies a range of factors which forecast future bond excess returns. Although his factors capture only 10% of the variation of bond excess returns in the following month, the trading strategy delivers Sharpe ratios in excess of 0.8.

We contribute to the literature in two dimensions. First, we test the framework introduced by Cochrane and Piazzesi (2005) in a multi-country setting. This enables us to test for the stability of their results across different countries. In particular, it is analyzed if the tent-shape of the factor loadings obtained when regressing bond excess returns on forward rates can be found in countries other than the USA. Our second contribution is the analysis of trading strategies which apply the forecasting model of Cochrane and Piazzesi (2005). The trading strategies are used to assess the degree of information stored in the yield curve in different curve regimes.

The remainder of this article is structured as follows. In Section 2 the methodology is introduced. A short description of our data is given in Section 3. The forecasting power of the forward curve for future bond excess returns is analyzed in Section 4. In Sections 5 and 6 unrestricted and restricted forecasting models are used to develop profitable trading strategies. This analysis is complemented in Section 7 by an analysis of the profitability of our strategy in single countries. Sections 8 and 9 study the link between the shape of the yield curve and the performance of our trading strategies. The conclusions are given in Section 10.

2. Methodology

Let P_t^n denote the price of a zero bond with a maturity of n years at time t. The one period return is

$$R_t^n = \ln\left(P_t^n\right) - \ln\left(P_{t-1}^{n+1}\right). \tag{1}$$

The forward rate at time t for a loan between $t+n-1$ and $t+n$ is expressed and calculated as

$$F_t^{(i-1)\to i} = \ln\left(P_t^i\right) - \ln\left(P_t^{(i-1)}\right). \tag{2}$$

For $i=1$ equation (2) becomes the 1 year spot rate. The bond return in excess of the risk free rate, c_t, is given by

$$RX_t^n = R_t^n - c_t. \tag{3}$$

As the strategies analyzed in this article are implemented using zero coupon swaps with a monthly reset of the floating leg we have reflected this in our notation. While (3) essentially describes the return of such a swap agreement, the average bond return across different maturities is calculated as

$$\overline{RX}_t^N = \frac{1}{N}\sum_{n=1}^{N} RX_t^n \ , \qquad (4)$$

where $N = 5$ for the purpose of this paper, i.e. we focus on the short end of the yield curve using a set of tenors ranging from 12 to 60 months in equal 12 month steps. Cochrane/Piazessi expressed future bond returns as a linear regression of realized excess returns versus one month lagged forward rates:

$$RX_{t+1}^n = \gamma_o + \sum_{i=1}^{N} \gamma_i F_t^{(i-1)\to i} + \varepsilon_{t+1}, \qquad (5)$$

with $\varepsilon_{t+1} \sim N(0,\sigma)$. We also run regressions with the average period return as dependent variable, i.e.

$$\begin{aligned} \overline{RX}_{t+1}^N &= \gamma_o + \sum_{i=1}^{N} \gamma_i F_t^{(i-1)\to i} + \varepsilon_{t+1} \\ &= \gamma_o + \gamma^T f_t + \varepsilon_{t+1}, \end{aligned} \qquad (6)$$

where $f_t = \left[F_t^{0\to 1}, F_t^{1\to 2}, ..., F_t^{4\to 5}\right]^T$. Let us define a single (state) variable that summarizes the information stored in current forward rates as $\Gamma_t = \gamma^T f_t$. We can now rerun a restricted version of (5). The parameters of this specification are estimated from

$$RX_{t+1}^n = \gamma_o + \eta\Gamma_t + \zeta_{t+1}, \qquad (7)$$

This second, restricted specification is used by Cochrane and Piazzesi (2005) to show that the single factor model's restrictions have only a minor impact on the forecasting ability of future bond returns. This illustrates that the forward curve contains a systematic component which forecasts expected bond returns across different maturities. In other words, the factor Γ_t is shown to be a state variable for expected returns of all maturities. Furthermore, the estimation of this restricted model reduces noise inherent in the estimation of the systematic component. After having estimated the forecasted future excess returns, $\widehat{RX}_{t+1}^n$, we will employ various portfolio construction methodologies.

Our first approach is to use Lehmann weighting, i.e. we set the portfolio weight of each bond equal to its forecasted return.[2] Note that we demean the signal (i.e. the forecasted return) in the cross section to enforce cash neutrality of our investment strategy. Hence the weight for country $j = 1,...,C$ is given by

[2] This weighting scheme has been credited to Lehmann (1990)

(8) $$w_{t,j} = \Psi_t \cdot \left(\widehat{RX}_{n,j}^{t+1} - \frac{1}{C}\sum_{j=1}^{C} \widehat{RX}_{n,j}^{t+1} \right),$$

where C stands for the total number of countries we invest in and Ψ_t is an aggressiveness factor that brings the portfolio up to the targeted risk level at time t.

The second approach is to build wing portfolios by equally over and underweighting bond markets with positive (negative) expected performance

(9) $$w_{t,j}^{wing} = \Lambda_t \begin{cases} +1 & \rho\left(signal_{t,j}\right) \geq \frac{n}{2} \\ -1 & \rho\left(signal_{t,j}\right) < \frac{n}{2}, \end{cases}$$

where Λ_t is a (different) risk scaling factor. For eight countries (9) will divide the universe into four long (short) positions of 100% (-100%) each. While the sum of these positions adds up to zero the risk that comes with these positions is adjusted by Λ_t to the required target level.[3]

In order to understand the variation in positions we calculate average turnover figures for the different strategies we test. Strategies with very low turnover tend to pick up on structural relations while a very large turnover might indicate a noisy signal. We define turnover (TO) as

(10) $$TO_t = \sum_{j=1}^{C} \left| w_{t,j} - w_{t-1,j} \right|.$$

Average turnover is calculated as $\overline{TO} = \frac{1}{T}\sum_{t=1}^{T} TO_t$, where T is the total number of periods in the sample.

3. Data

The article studies the forecasting power of forward rates for future zero coupon bond excess returns in 7 countries (Australia, Canada, Germany, Japan, Switzerland, UK, and USA). The trading strategies are implemented with swaps on the respective zero coupon bonds. Swaps have the advantage of low transaction costs and the possibility to go long and short in the fixed rate easily. Since the Japanese fixed income market possesses a range of particularities – among others very low interest rates and a long time frame of deflation – our strategies are tested for robustness by analyzing their profitability in investment universes with and without Japan. The zero coupon yield curves are obtained from Datastream which provides information in the form of inputs for (1) and (2). As this

[3] Equation (9) can easily be adjusted for an uneven set of countries or more concentrated wings.

article focuses on the implementation of the previous model in a trading strategy (where frequent updates of positions are desirable), monthly returns are used. For the risk free rate we use the 1-month inter-bank rates of the respective countries. The dependent variables are the 1-year zero rate and the 1-year forward rates starting 1, 2, 3, and 4 years in the future. This data reflects the yield curve until a maturity of 5 years. The data in this article covers a time frame from February 1997 to July 207.

4. Statistical Significance: The Forecasting Power of the Forward Curve for Future Bond Returns

Cochrane and Piazzesi (2005) use the forward curve to forecast the bond returns 12 months ahead and reach R^2 's of around 0.35. Using the unrestricted specification (5) for $n = 5$, i.e. on five year zero bonds, we repeat their analysis for the seven countries in our sample. The results are summarized in Table 1. First note that we obtain high R^2 's between 0.38 for Switzerland and 0.69 for Canada. This is hardly surprising since we have used overlapping data.

Table 1. International Forecasting Power of the Cochrane / Piazzesi (2005) specification. We use equation (5), where the dependent variable is the 12 month bond return on a 5 year zero bond. The numbers below the parameter values denotes denotes the respective t-values.

Parameter	AUS	CAN	GER	JAP	CH	UK	USA
γ_0	-0.29	-0.16	-0.12	-0.03	-0.11	-0.13	-0.26
	-6.99	*-7.28*	*-6.80*	*-6.22*	*-5.45*	*-6.19*	*-8.26*
γ_1	-19.45	-19.41	-46.18	37.67	-36.38	-60.99	-22.73
	-1.89	*-2.89*	*-2.52*	*2.50*	*-3.14*	*-6.50*	*-2.83*
γ_2	80.44	-5.02	18.91	-24.48	22.99	149.05	-51.80
	2.41	*-0.56*	*0.36*	*-1.68*	*1.09*	*5.35*	*-2.33*
γ_3	28.44	72.00	33.55	-28.58	47.24	-100.94	91.14
	0.52	*4.44*	*0.58*	*-1.81*	*2.53*	*-2.73*	*2.56*
γ_4	-145.05	-68.22	54.75	22.16	-41.97	-34.14	65.20
	-2.34	*-1.75*	*2.65*	*2.10*	*-1.38*	*-0.79*	*4.28*
γ_5	121.48	59.79	-28.58	37.25	49.09	78.50	-27.11
	3.25	*2.01*	*-1.00*	*4.06*	*2.05*	*3.00*	*-1.08*
R^2	0.67	0.69	0.51	0.55	0.38	0.55	0.65

The parameter on $F_t^{0\to1}$ (one year yield), is predominantly negative. Only for Japan a positive parameter, γ_1, is found. For all other countries it is significantly different from zero at least at the 10% level. Somewhat surprisingly, this result indicates lower returns for five year bonds if the short term yield is higher. For $F_t^{1\to2}$ (i.e., the forward rate starting in 12 months for an investment ending in 24 months), the sign depends on the country. The parameter is negative for Canada, Japan, and the USA. Only for Japan and the USA the parameter is significantly negative (t-statistics of -1.68 and -2.33). For the rates $F_t^{2\to 3}$ and $F_t^{3\to 4}$ we also obtain mixed results and there does not appear to be a consistent and systematic impact on the future returns of zero bonds in the countries in our sample. Finally, for the $F_t^{4\to 5}$ rate we obtain predominantly positive parameters. Only for Germany and the USA negative parameters are obtained, but they are not significantly different from zero. The positive parameters for Australia, Canada, Japan, Switzerland, and the UK are highly significant though (t-statistics of 3.25, 2.01, 4.06, 2.05, and 3.00). Thus, higher $F_t^{4\to 5}$ rates are an indicator for higher returns of zero bonds with a maturity of 5 years.

Table 2: International Forecasting Power of the Cochrane / Piazzesi (2005) specification. We use equation (5), where the dependent variable is the one month bond return on a 5 year zero bond. The numbers below the parameter values denotes the respective t-values.

Parameter	AUS	CAN	GER	JAP	CH	UK	USA
γ_o	-0.03	-0.02	-0.01	-0.01	-0.01	-0.02	-0.04
	-1.60	*-1.79*	*-1.77*	*-2.52*	*-2.26*	*-3.32*	*-3.14*
γ_1	9.06	-2.24	4.43	11.58	-4.50	3.34	-5.98
	1.85	*-0.59*	*0.80*	*1.76*	*-1.33*	*0.99*	*-1.90*
γ_2	-35.91	-2.59	-12.03	-6.95	8.14	-11.19	12.88
	-2.27	*-0.51*	*-0.74*	*-1.00*	*1.34*	*-1.13*	*1.43*
γ_3	53.21	22.12	4.77	-8.97	-10.54	-4.53	-21.39
	2.13	*2.36*	*0.27*	*-1.19*	*-1.92*	*-0.34*	*-1.47*
γ_4	-41.68	-27.41	9.03	3.46	4.39	18.69	18.10
	-1.55	*-1.26*	*1.40*	*0.77*	*0.49*	*1.21*	*2.91*
γ_5	21.06	14.65	-3.57	8.47	6.04	-0.64	4.42
	1.27	*0.92*	*-0.41*	*2.15*	*0.87*	*-0.07*	*0.43*
R^2	0.12	0.12	0.07	0.10	0.11	0.10	0.16

Cochrane and Piazzesi (2005) report that the estimated parameters exhibit a tent shape. In our analysis we do not find direct evidence for such a tent shape. In fact, for the 12 month return forecasts, we do not find any systematic pattern across countries. We also analyze the parameters of zero bonds with one to four years of maturity, but cannot find a tent shape pattern either. This gives evidence that the results of Cochrane and Piazzesi are not transferable to other countries and time frames than the one they studied. Additionally, the lack of a pattern in the estimates of the forward rate parameters across countries indicates that there is not a systematic, uniform effect of the forward rate curve on the future bond returns. However the R^2's indicates, that there is a strong link between the forward curve and the bond returns. The analysis is even more difficult given that all explaining variables are highly correlated. This prevents us from a stable estimation of the parameters in our limited sample. The correlations of the explaining variables are higher than 0.4 for all factors and all countries.[4] For the UK the correlations are particularly high, ranging between 0.81 for $\rho\left(F_t^{o\to 1}, F_t^{4\to 5}\right)$ and 0.98 for $\rho\left(F_t^{3\to 4}, F_t^{4\to 5}\right)$. Even if there would be economic factors governing the impact of the different forward rates on future bond returns, it would be difficult to identify them robustly given the high correlations. Thus, high correlations among the explaining variables might be one of the reasons for the missing pattern of the estimated parameters across the countries in our sample. In short, specification (5) appears problematic from an econometric point of view.

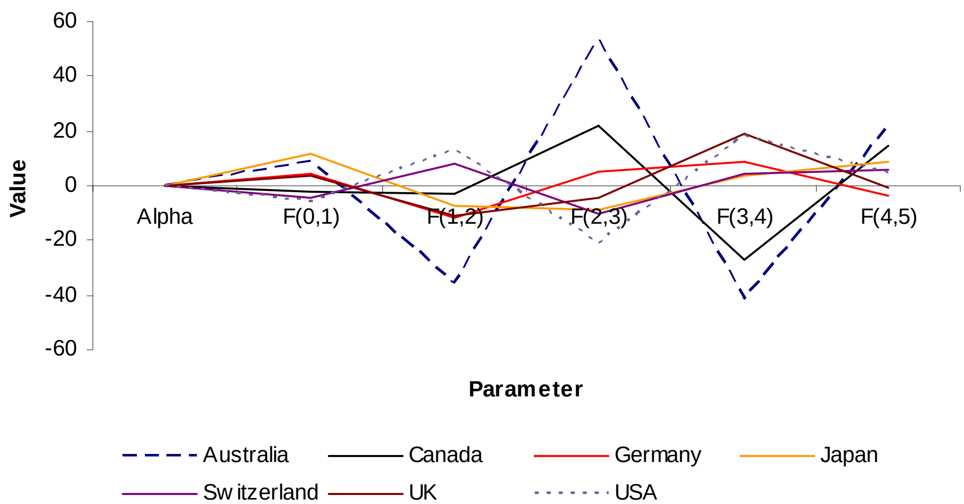

Figure 1: Parameter estimates for the standard model and a 1-month forecasting horizon. This graph depicts the parameter estimates for the standard forecasting model using specification (5). The forecasting horizon is 1 month.

As can be seen in Table 2, the forecasting power of the forward curve for the bond returns one month ahead is much lower (R^2 between 0.07 for Germany and 0.16 for the US). Therefore, the forecasting power of the forward curve increases as the forecasting horizon increases. There is even less evidence for a pattern of the estimated parameters which is consistent across the different countries in the sample (compare Figure 1).

[4] For details on correlations please refer to the appendix.

Table 3: International forecasting power of the *restricted* Cochrane / Piazzesi (2005) specification in (7)**.** The dependent variable is the *12 month* excess bond return.

Parameter	AUS	CAN	GER	JAP	CH	UK	USA
γ_o	-0.28	-0.17	-0.13	-0.03	-0.10	-0.12	-0.26
	-12.38	-10.72	-8.95	-6.22	-6.64	-10.08	-12.78
η	1.36	1.25	1.47	1.66	1.40	1.41	1.32
	12.90	12.90	10.73	10.44	8.20	11.41	14.32
R^2	0.66	0.66	0.51	0.52	0.38	0.54	0.65

Forecasting with the restricted model of Equation (7), similar results are obtained.[5] For a forecasting horizon of 12 months, the R^2's range between 0.3774 for Switzerland and 0.6620 for Canada as can be seen from Table 3. These figures are similar to the ones obtained for the non-restricted model. The restricted parameter is highly statistically significant with t-statistics being above 8 for all countries. The parameter is for all countries in a range between 8 and 14, which is an indicator that the effect of the systematic factor on the future bond returns is similar across all countries in the sample.

Table 4: International forecasting power of the *restricted* Cochrane / Piazzesi (2005) specification in *(7)*. The dependent variable is the *one month* excess bond return.

Parameter	AUS	CAN	GER	JAP	CH	UK	USA
γ_o	-0.03	-0.02	-0.01	0.00	-0.01	-0.02	-0.04
	-3.48	-3.21	-2.47	-2.25	-3.20	-3.45	-4.53
η	1.44	1.37	1.54	1.34	1.64	1.65	1.45
	3.55	3.56	2.97	3.05	3.70	3.62	4.86
R^2	0.12	0.12	0.07	0.08	0.10	0.10	0.16

Once a forecasting horizon of one month is chosen, the forecasting power is reduced. The results are given in Table 4. We arrive at R^2's below 0.17 confirming the results obtained for the unrestricted case. The model performs best for the USA (R^2 of 0.16) and worst for Japan (R^2 of 0.08). Although the parameters are still significant at the 1% level, the t-statistics are reduced compared to the 12 month return forecasts (t-statistics range between 2.97 for Germany and 4.86 for the USA). The parameter values for the restricted

[5] The restricted forecasting specification (7) uses an aggregate factor which is determined through the parameters γ_0 to γ_5. As in Cochrane and Piazzesi (2005), these parameters are estimated using the whole dataset and are constant over time. However, this is equal to assuming that the information of the whole dataset is known at each point in time during the analysis and is equal to assuming perfect foresight. Such an approach might induce an in-sample estimation bias. In Section 6 we analyze this in-sample estimation bias more thoroughly and compare the results to a rolling estimation of the parameters for the restricted factor.

factor Γ are all positive and range from 1.34 (Japan) to 1.65 (UK), indicating that the reaction of future bond returns to the systematic factor has a similar magnitude across the countries. The fact that the explanatory power of the restricted model is similar to the unrestricted model, indicates that the restricted factor is actually a good proxy for the information contained in the forward curve. This result confirms Cochrane and Piazzesi (2005).[6]

In summary, using the forward curve to forecast future bond excess returns works best for the US bond market, but delivers reasonable results for all countries in the sample. Once the approach is changed from overlapping 12-month return forecasting horizons to a 1-month forecasting horizon, the explanatory power of the forward curve for future bond returns is reduced significantly for the studied universe.

5. Economic Significance: The Profitability of the Unrestricted Forecasting Model

We now move from investigating statistical significance to economic significance. Using the standard specification in equation (5), we test various trading strategies. Until otherwise noted, the bond tenor is 5 years and the investment positions are chosen using the return forecasts in a Lehmann (1990) based weighting scheme. In order to calibrate our strategy we move along two dimensions: Varying time horizon for rolling regressions (36 and 60 month) as well as the choice of universe (with and without Japan). Our results are summarized in Table 5. We find that a rolling estimation period of 60 months (i.e., the rolling regressions use a window of 60 months to estimate the parameters) for the forecasting appears to be more robust than the shorter 36 months. Dropping Japan out of the spectrum of countries results in a higher information ratio (IR) for both estimation periods of 36 (from 0.66 to 0.72) and 60 months (from 0.74 to 0.90). The highest t-statistic for the average strategy return is obtained for an estimation period of 60 months without Japan (t-statistic of 2.07). In general, we can confirm that the forward curve does have forecasting power for future bond returns and that this can be used to generate profitable trading strategies. For an estimation period of 60 months the turnover of the strategies is around 0.55. This indicates that transaction costs should not cause a large threat to the profitability of the strategy.[7]

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[6] Note that the regressions used above involve a stationary left hand side variable (zero bond excess returns) and individually non-stationary right hand side variables (forward rates). From an econometric point of view it is well known that the trending right hand side variables might just pick up a trend in the left hand variable and as such any relationship might be spurious. See Ferson et al. (2003) for a review of using non-stationary variables in return forecasting regression and its remedies. However we believe the problem is less serious in our example as the right hand side variables are likely to be jointly stationary (i.e. cointegrated) and the positions we get in the constructed portfolios considerably change sign, i.e. are not structural. It is equally well known that slowly moving explanatory variables will lead to biased parameter estimates. Hence we are not interested in statistical measures of forecasting ability (which are subject to these criticism) but on economic profitability.

[7] For the countries in our sample liquid zero coupon swaps are available. The spread which is charged by investment banks is generally around 0.3 basis points (bps). Given that zero coupon bonds with a tenor of 5 years have a duration of 5, the transaction costs translate into a price impact of around 0.3 * 5 = 1.5 bps per contract. For the best performing strategy in Table 5 a turnover of 0.55 is measured. Multiplying this turnover figure with the price impact of 1.5 bps we arrive at a performance drag of 0.825 bps per month.

Table 5. Lehmann weightings. The table contains the results of the standard Cochrane/Piazzesi specification implemented with a Lehmann weights portfolio. Regression forecasts are based on (5) combined with weighting scheme (8). The forecasting horizon for the bond returns is 1 month. The parameter μ stands for the monthly mean return, σ for the volatility, IR for the information ratio, TO for the turnover, and T for the total number of periods the strategy is analyzed.

Universe	Total	No Japan	Total	No Japan
	60	60	36	36
μ	0.06%	0.07%	0.06%	0.06%
σ	0.27%	0.27%	0.29%	0.29%
$t-value$	1.72	2.07	1.80	1.96
IR	0.74	0.90	0.66	0.72
TO	0.50	0.55	0.70	0.72
T	64	64	88	88

The choice of Lehmann weights is uncritical for the performance of the strategies. In fact, choosing equally weighted portfolio going long and short an equal number of countries with the highest and lowest forecast, respectively, can improve the performance (compare Table 6). The number of countries we go long (short) is termed wing size.

Table 6: **Results using Equally Weighted Cash-Neutral Portfolios.** The table contains the results of the standard Cochrane/Piazzesi specification implemented with equally weighted portfolios of different wing sizes. The forecasting horizon for the bond returns is 1 month. The estimation period is 60 months. The parameter μ stands for the monthly mean return, σ for the volatility, IR for the information ratio, TO for the turnover, and T for the total number of periods the strategy is analyzed.

Universe	Total	No Japan	Total	No Japan	Total	No Japan
Wing Size	1	1	2	2	3	3
μ	0.05%	0.05%	0.06%	0.08%	0.05%	0.08%
σ	0.29%	0.29%	0.28%	0.26%	0.26%	0.26%
$t-value$	1.35	1.51	1.80	2.34	1.53	2.43
IR	0.58	0.65	0.78	1.01	0.66	1.05
TO	0.57	0.55	0.54	0.48	0.50	0.45
T	64	64	64	64	64	64

Using the whole range of countries the information ratio rises for a wing size of 2 (from 0.74 for the Lehmann weights to 0.78 for a wing size of 2). For the strategy without Japan

This translates in a deterioration of the IR from 0.90 to 0.79. By optimizing our weighting mechanism with respect to transaction costs, the impact could be reduced even further. Thus, although transaction costs have an impact on performance, the strategy remains profitable.

the results are mixed, but for a wing size of 2 and 3 we obtain an increase in performance (*IR* of 1.01 and 1.05, respectively, compared to 0.90 for the Lehmann weights).

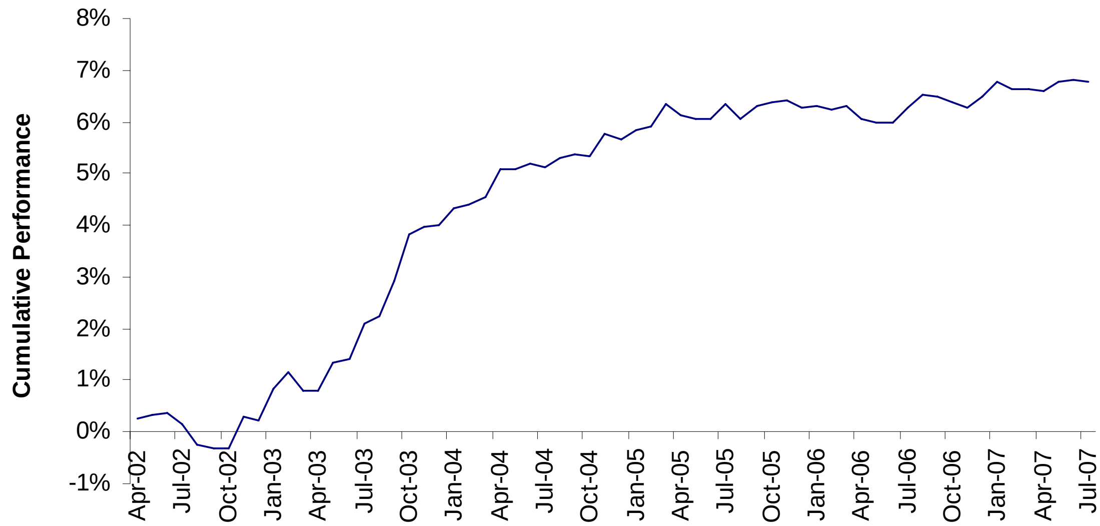


Figure 2: Cumulative Performance of the Modified Cochrane/Piazzesi Approach with Lehmann Weights. This graph contains the cumulative performance of the Modified Cochrane/Piazzesi Approach in specifications (11) and (12). The investment universe contains all countries.

So far we tested straightforward variations of the US centric version of the Cochrane/Piazesssi model. However, the US financial markets are well known to lead other national financial markets. This spill-over effect from US forward rates motivates us to try another specification (we term this specification "Modified Cochrane/Piazzesi") using the US forward rate for all countries in the sample. In the Modified Cochrane/Piazzesi specification there are no changes for the US:

(11) $$RX^n_{t+1,US} = \gamma_o + \sum_{i=1}^N \gamma_i F_{t,US}^{(i-1)\to i} + \varepsilon_{t+1},$$

while the specification for all other countries follows

(12) $$RX^n_{t+1,j} = \gamma_o + \sum_{i=1}^N \gamma_i F_{t,j}^{(i-1)\to i} + \kappa F_{t,US}^{4\to 5} + \varepsilon_{t+1},$$

incorporating the forward rate $F_{t,US}^{4\to 5}$ of the US fixed income market. Trading strategies exploiting this specification are very profitable. Using Lehmann weights the IR of the standard case achieves 1.41 (compare Table 7). Figure 2 illustrates the cumulative performance of this strategy. The performance was the strongest from mid-2002 until mid-2005. Afterwards the performance got weaker, but the graph still shows a constantly upwards sloping cumulative performance. Dropping Japan out of the spectrum of countries increases our IR to 1.50. Unlike the standard case, the usage of equally weighted long/short portfolios does not improve the performance of the strategy. For a strategy without Japan, the performance actually decreases notably (IR of 1.05 for the standard case applying specification (5) as compared to 0.88 for the Modified Cochrane/Piazzesi specification and a wing size of 3).

Table 7: Results Using the Modified Cochrane/Pizzesi Specification for the Return Forecasting. This strategy uses the specification detailed in equations (12) and (13) for the forecasting of bond returns. The strategy applies Lehmann weights and equally weighted portfolios with a wing size of 3. The forecasting horizon for the bond returns is 1 month. The strategy is implemented by using zero coupon bonds with a tenor of 60 months. The estimation period is 60 months

Weighting	Lehmann		Equal Weighting Wing Size of 3	
Universe	Total	No Japan	Total	No Japan
μ	0.11%	0.12%	0.05%	0.07%
σ	0.26%	0.28%	0.27%	0.28%
$t-value$	3.25	3.47	1.50	2.03
IR	1.41	1.50	0.65	0.88
TO	0.58	0.60	0.55	0.42
T	64	64	64	64

As Ilmanen (1997) and Cochrane and Piazzesi (2005) state, the forecasting power of their models for bond returns increases once the forecasting period increases. In a variation of our trading strategy we forecast bond returns one year ahead. These forecasts are updated every month. We invest each month $1/12^{th}$ of the total capital in the optimal weights of the month and hold the respective portfolio for 12 months. Such an updating mechanism for portfolio weights is widely used (compare, e.g., Jegadeesh and Titman (1993) for a more detailed description). This way we can actually use the information obtained by forecasting the expected bond excess returns for one year ahead, but we can also benefit from a rolling update of the information. The results of this strategy are summarized in Table 8.

Table 8: Results Using Lehmann Weights and Different Bond Return Forecasting Methodologies. The table contains the results when trading on a range of forecasting methodologies. The forecasting period is 12 month and the portfolios are updated monthly. The total wealth is invested to one twelfth according to the signal in a respective month and held for 12 month. This way information is updated in a rolling fashion. Forecasting mechanism (5) is the standard Cochrane/Piazzesi approach and mechanism (11) uses the US 5 year forward rate in the forecasting equation for all countries. The estimation period is 60 months. The weights are determined according to Lehmann (1990).

Forecasting Mechanism	(5)		(11)	
Universe	Total	No Japan	Total	No Japan

μ	0.01%	0.00%	0.05%	0.05%
σ	0.24%	0.24%	0.28%	0.28%
$t-value$	0.22	-0.01	1.45	1.21
IR	0.11	-0.01	0.69	0.57
TO	0.13	0.14	0.13	0.13
T	53	53	53	53

Interestingly, we do not find a higher IR when we use a 12 month forecasting horizon. Although there is evidence that longer forecasting periods raise the R^2 of the respective forecasting regressions, this cannot be translated in higher IRs of the respective strategies. Thus, it appears advisable to use a one month forecasting horizon. Specification (11) returns the best results, delivering a maximum information ratio of 0.69. The results for forecasts of one month indicate a turnover of around 50% per month. For the forecasts of 12 months, turnover figures are between 0.13 and 0.14. The strong decrease in performance could therefore be linked to a higher persistence of the portfolio weights and a lower responsiveness to shorter term aspects of bond valuation, caused by the longer forecasting horizon.

Table 9: Results Using Lehmann Weights to Forecast Returns for Different Horizons. The table contains the results of the standard Cochrane/Piazzesi specification implemented with a Lehmann weights portfolio. Regression forecasts are based on (5) and implemented with weighting scheme (8). The forecasting horizon for the bond returns is increased from 1 to 18 months. The strategy is implemented by using zero coupon bonds with a tenor of 60 months. The estimation period is 60 months.

Forecasting Horizon	1	3	6	9	12	18
μ	0.06%	0.02%	0.01%	0.01%	0.01%	-0.02%
σ	0.27%	0.29%	0.27%	0.25%	0.24%	0.24%
t-statistic	1.72	0.48	0.33	0.25	0.22	-0.70
IR	0.74	0.21	0.15	0.12	0.11	-0.35
TO	0.50	0.24	0.20	0.16	0.13	0.10
T	64	62	59	56	53	47

The impact of a longer bond return forecasting horizon on the returns of the strategy is analyzed by increasing the forecasting horizon from one to 18 months for the standard Cochrane/Piazzesi specification. The results can be found inTable 9. The performance of the strategy decays relatively rapidly. While a one month forecasting horizon returns a considerable information ratio of 0.74, a three month forecasting period has already a significantly lower performance (information ratio of 0.21). As we increase the forecasting horizon, the information ratio of the strategy decreases consistently and reaches a low of -0.35 for a forecasting horizon of 18 months. The turnover decreases monotonously with the information ratio. This supports our hypothesis that a longer forecasting horizon leads to more stable weights and a reduced possibility to take advantage of the return forecasts in a tactical asset allocation strategy.

Up to now we used a bond tenor of 5 years for the dependent variable. We tested our results for stability using bond tenors from 1 to 10 years. The results of this analysis are summarized in Table 10.

Table 10: Results Using the Modified Cochrane/Piazzesi Approach for the Return Forecasting on Different Bond Tenors. This strategy uses the specification detailed in equations (11) and (12) for the forecasting of bond returns. The strategy is implemented with Lehmann weights. The forecasting horizon for the zero coupon bond returns is 1 month and the estimation period is 60 months. The universe is composed of all countries in the sample. The parameter μ stands for the monthly mean return, σ for the volatility, *IR* for the information ratio, *TO* for the turnover, *T* for the total number of periods the strategy is analyzed, and *n* for the bond tenor in months.

Bond Tenor	1	2	3	4	5	10
μ	0.03%	0.08%	0.08%	0.12%	0.11%	0.09%
σ	0.19%	0.26%	0.23%	0.26%	0.26%	0.28%
$t-value$	1.37	2.47	2.87	3.61	3.25	2.62
IR	0.59	1.07	1.24	1.56	1.41	1.13
TO	2.79	1.56	0.91	0.74	0.58	0.30
T	64	64	64	64	64	64

The trading strategies with different tenors show a consistent performance. The best performance is obtained for a tenor of 4 years (IR of 1.56). However, the 5 year tenor used up to now delivers the second highest IR of 1.41. Interestingly, turnover decreases with an increasing length of bond tenor. Apparently the forecasts are more stable for longer bond tenors.

In summary, the forward curve contains information which can be used in profitable fixed income trading strategies. The strategy performance remains strong across different weighting mechanisms. An alternative specification using the US forward rates to forecast bond returns in other countries delivered the best performance. The best trading strategy performance is achieved when using a bond return forecasting horizon of one month.

6. Economic Significance: The Profitability of the Restricted Forecasting Model

We now test the economic performance achieved when investing according to the return forecasts of the restricted model. In other words: how much excess return can be generated by using a single "state variable" for each country. For the restricted model all parameters γ_1 to γ_5 have to be estimated to determine the restricted factor Γ. As in Cochrane and Piazzesi (2005), the parameters are estimated once for the whole time frame using the entire sample data. The strategy performance which results from using this in-sample forecasting approach is tabulated in Table 11. The IRs are higher than 1.60 and, therefore, the static restricted model appears to have the best forecasting power of all the strategies considered up to this point. The highest IR of 1.87 is obtained using all countries in the sample. The turnover is at a reasonable level around 0.60. However, the estimation of the factors in a static way uses information which is not yet revealed in a real-time trading environment (i.e., the static approach assumes perfect foresight when estimating the parameters for the restricted factor). Possibly this leads to an in-sample forecasting, overestimating the performance which can actually be achieved with this restricted model.

Table 11: Performance of Strategies using the Restricted Cochrane / Piazzesi Specification in Equation (7) (*static factor generation*). The table contains the results of the restricted Cochrane/Piazzesi specification implemented with a Lehmann weights portfolio. The forecasting horizon for the bond returns is 1 month. The strategy is implemented by using zero coupon bonds with a tenor of 60 months. The estimation period is 60 months.

Universe	Total	No Japan
μ	0.14%	0.13%
σ	0.26%	0.28%
$t-value$	4.31	3.77
IR	1.87	1.63
TO	0.56	0.60
T	64	64

When testing trading strategies, it makes more sense to estimate the weighting parameters γ_1 to γ_5 for the restricted factor Γ with a rolling window, recalibrating the model once new data becomes available. Therefore, we test the performance of the restricted model again by using a rolling window in the estimation of the systematic factor. The results are shown in Table 12. Note, that the performance of the original restricted specification is greatly reduced. The information ratios for the two variations of the rolling restricted model are around 0.80. The highest IR is obtained for the reduced universe (IR of 0.82). This result indicates that the strong performance of the static restricted model is largely driven by a bias introduced through in-sample forecasting. Therefore, the model has to be used with caution and appears to be dominated by the unrestricted models. This result questions the in-sample forecasting approach for the restricted factor which is chosen in Cochrane and Piazzesi (2005) and adds to a deeper understanding of the information contained in the forward curve.

Table 12: Performance of Strategies using the Restricted Cochrane / Piazzesi Specification in Equation (7) (*rolling factor generation*). The table contains the results of the restricted Cochrane/Piazzesi specification implemented with a Lehmann weights portfolio. The forecasting horizon for the bond returns is 1 month. The strategy is implemented by using zero coupon bonds with a tenor of 60 months. The estimation period is 60 months. The restricted Cochrane/Piazzesi variable is generated with variable weights for the forward rates. The weights, for the forward rates are estimated using a rolling 60-month window of data.

Universe	Total	No Japan
μ	0.06%	0.06%

σ	0.26%	0.27%
$t-value$	1.85	1.89
IR	0.80	0.82
TO	0.51	0.55
T	64	64

Cochrane and Piazzesi (2005) claim that the restricted factor is unrelated to the level, slope, and curvature of the yield curve. We analyze the rolling restricted factor Γ to test this hypothesis for international bond markets. We start this analysis using *level, slope* and *curvature* of the yield curve to forecast future excess returns. We define these factors as

(13) $$level_{t,j} = y^1_{t,j}, \qquad slope_{t,j} = y^{10}_{t,j} - y^1_{t,j}, \qquad curve_{t,j} = y^{\frac{10-1}{2}}_{t,j} - \frac{1}{2}\left(y^{10}_{t,j} + y^1_{t,j}\right).$$

for each country j and time t and use the linear regression equation

(14) $$RX^n_{t+1,j} = \beta_o + \beta_1 level_{t,j} + \beta_2 slope_{t,j} + \beta_3 curve_{t,j} + \varepsilon_{t+1,j}.$$

Forecasting the future excess returns with *level, slope*, and *curvature* and applying Lehmann weights leads to profitable trading strategies. The performance lags behind our previous results though. Table 13 summarizes the results.

Table 13: Performance of Trading Strategies using *level*, *slope*, *curvature* and the Restricted Cochrane / Piazzesi Factor. The table contains the results of using level, slope, curvature, and the Restricted Cochrane / Piazzesi factor to forecast bond returns. The strategy is implemented with a Lehmann weights portfolio. The forecasting horizon for the bond returns is 1 month. The strategy is implemented by using zero coupon bonds with a tenor of 60 months. The restricted Cochrane/Piazzesi variable is determined by a rolling factor generation. In other words, the weights for the different forward rates in the restricted factor are estimated using a rolling 60-month window of data.

Explanatory Variables	*Level, Slope, Curvature*	*Level, Slope*	*Level, Slope, Curvature,* Γ
μ	0.04%	0.06%	0.05%
σ	0.30%	0.28%	0.27%
$t-value$	1.09	1.70	1.54
IR	0.47	0.74	0.67
TO	0.48	0.31	0.64
T	64	64	64

In our sample, the pair-wise correlation of the rolling restricted factor with the level, slope, and curvature of a particular country is in general between 0.3 and 0.6 (compare Table 20). A particularly strong correlation is found for the Japanese restricted factor, which has a correlation of 0.63 and 0.49 with the *level* and *slope*, respectively. For other countries similarly high correlations are found.

A further analysis of the link between the restricted factor Γ and the yield curve factors is performed by regressing the rolling restricted factor on the *level, slope*, and *curvature* of the yield curve (compare Table 14). The R^2 's of the regressions range from 0.34 (for Australia) to 0.74 (for Japan). For all countries a significantly positive parameter (at least at the 10% level) is obtained for the *level* and *slope* of the yield curve. The *curvature* has a significant (at the 10% level) parameter in 6 out of 7 countries. This analysis indicates that the restricted factor introduced in Cochrane / Piazzesi (2005) is by no means independent from the shape of the term structure of yields.

Table 14: Regression of the Restricted Cochrane / Piazzesi Factor (Γ) on *level*, *slope*, and *curvature* of the Yield Curve. This table contains the results of regressing the rolling restricted Cochrane / Piazzesi factor on the level, slope, and curvature of the yield curve.

Parameter	AUS	CAN	GER	JAP	CH	UK	USA
β_o	0.00	0.00	0.00	0.00	0.00	0.00	0.01
	-0.80	*1.12*	*-2.01*	*-3.31*	*-1.03*	*4.33*	*5.77*
β_1	4.40	2.93	1.94	5.36	2.54	2.74	3.19
	6.52	*6.07*	*13.14*	*14.40*	*14.60*	*16.84*	*9.07*
β_2	5.77	3.79	3.25	4.12	4.08	4.47	1.65
	3.53	*3.55*	*10.60*	*11.85*	*13.65*	*11.40*	*1.65*
β_3	-6.37	1.64	-4.07	-5.99	2.25	-3.17	16.00
	-1.65	*0.53*	*-3.64*	*-6.60*	*2.16*	*-3.68*	*6.02*
R^2	0.34	0.51	0.65	0.74	0.73	0.70	0.72

This evidence is further solidified when implementing an investment strategy using the information contained in the yield curve and the forward curve. This analysis is implemented by running a regression using *level, slope, curvature*, and the restricted, out-of-sample $\Gamma_{t,j}$ factor (i.e., the factor is estimated with a rolling window and without the in-sample estimation bias) as forecasting variables:

(15) $$RX^n_{t+1,j} = \beta_o + \beta_1 level_{t,j} + \beta_2 slope_{t,j} + \beta_3 curve_{t,j} + \eta_j \Gamma_{t,j} + \varepsilon_{t+1,j} .$$

When using level and slope alone, we arrive at an IR of 0.74. This performance is even better than the one obtained from using *level, slope*, and *curvature* together with the restricted Cochrane / Piazzesi factor (IR of 0.67). Therefore, the performance of the trading strategy cannot be improved by this approach. This indicates that the restricted factor Γ has only limited additional information content if used for forecasting together with the yield curve shape factors.

We also studied the impact of filters on the performance of the strategy. Filters are applied by imposing a threshold on the absolute value of the forecast which has to be exceeded before an investment takes place. However, imposing filters does not improve the performance of the strategy significantly.

In this section we found that the static estimation of the restricted factor is subject to an in-sample bias and does not perform as well anymore when estimated in a rolling fashion. Furthermore, the restricted factor is highly correlated to the yield curve factors and provides little additional information to increase the profitability of trading strategies.

7. The Profitability of Signals on a Country by Country Basis

After having seen that the model by Cochrane and Piazzesi (2005) can forecast bond returns and profitable trading strategies can be implemented with this knowledge, we study how well the signal works for different countries. The strategy in each country is implemented by forecasting the returns of a specific country. Then we go long or short in that country depending on whether the forecasted return is positive or negative, respectively. The performance of the strategy in the different countries of our sample is summarized in Table 15. The results indicate that the performance of specification (5) is mixed. While it works well for the US (IR of 0.97), the performance for Germany, Switzerland, and the UK is relatively bad (IR's of -0.91, -0.71, and -0.72, respectively). Not surprisingly, a negative IR (-0.19) is obtained by equally weighting investments in the seven countries. For the restricted model the performance is better. For Australia, Switzerland, and the USA the performance is particularly good with IR's of 0.61, 0.84, and 0.72, respectively. This approach delivers a reasonable performance when implementing a portfolio with equal weighting in the strategy for each country (IR of 0.56). However, for four of the seven countries the IR is negative (i.e., for Canada, Germany, Japan, and the UK). Therefore, on a single country basis there is no clear preference whether to use the restricted or unrestricted model.

Table 15: Performance of Different Strategies Implemented in Each Country Separately. The table contains the results when trading on a range of forecasting methodologies. The forecasts are for the next month. We implement the strategies in each month separately, going long in an index if positive returns are forecasted and short otherwise. Forecasting specification (5) is the standard Cochrane / Piazzesi approach, specification (7) uses the restricted Cochrane / Piazzesi factor with a rolling update, and specification (12) uses the US 5 year forward rate in the forecasting equation for all countries. The estimation period is 60 months. The equally weighted portfolio is the return obtained when investing an equal amount of money in the single country strategies.

Forecasting Specification		AUS	CAN	GER	JAP	CH	UK	USA	Equally Weighted Portfolio
(5)	μ	0.07%	0.07%	-0.25%	0.06%	-0.17%	-0.19%	0.43%	-0.02%
	σ	0.77%	0.92%	0.94%	0.62%	0.83%	0.92%	1.53%	0.43%
	IR	0.30	0.28	-0.91	0.34	-0.71	-0.72	0.97	-0.19
(7)	μ	0.13%	-0.06%	-0.10%	-0.05%	0.20%	-0.07%	0.32%	0.07%

	σ	0.76%	0.92%	0.97%	0.62%	0.82%	0.94%	1.55%	0.43%
	IR	0.61	-0.22	-0.35	-0.28	0.84	-0.26	0.72	0.56
(12)	μ	0.07%	-0.04%	0.12%	0.13%	0.15%	0.12%	0.56%	0.23%
	σ	0.77%	0.93%	0.97%	0.61%	0.83%	0.94%	1.47%	0.64%
	IR	0.31	-0.16	0.43	0.76	0.65	0.43	1.33	1.24

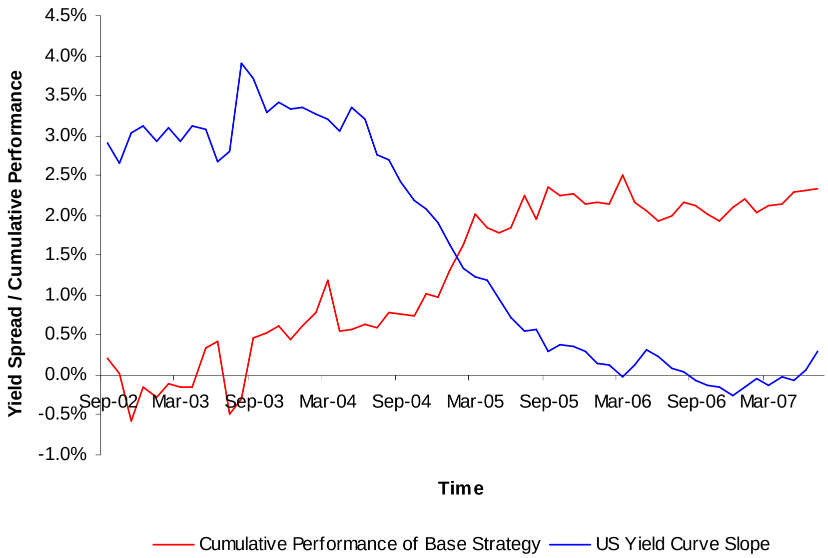
The modified Cochrane and Piazzesi approach (equation 13) also delivers good results. For the US the achieved IR is particularly high (IR of 1.33). The other IR's are mostly positive and range between -0.16 for Canada and 0.76 for Japan. Applying specification (13) in each country separately and forming an equally weighted portfolio results in a high IR of 1.24.

8. Regression of Total Strategy Performance on US Yield Curve Components

The previous sections found that the yield curve can be used to predict future bond returns. Our analyses show that the profitability of this strategy was high in the overall period, but reduced lately. This section studies if the shape of the yield curve has an impact on the performance of the fixed income trading strategies analyzed this far. Ultimately, we analyze how much the forecasting ability of the Cochrane / Piazzesi model is linked to the shape of the yield curve. Given that future economic growth is a driver of financial markets and often linked to the shape of the yield curve such a link would be consistent with previous research.[8]

Figure 3: Performance of the Base Case Strategy and the US Yield Curve Slope. This graph depicts the yield curve slope and the performance of the base case strategy. The base case strategy invests in Lehmann weights according to bond price return forecasts from specification (5).

[8] Compare, among others, Harvey (1989, 1991).



With the US economy and capital market being dominant in the world markets, the US yield curve is the best choice to link strategy returns and curve components. Figure 3 depicts the *slope* of the US yield curve and the performance of the base case using equation (5) for the return forecast (compare the first column of Table 5). The two time series appear to be a mirror image of each other. The cumulative performance increases when the yield curve *slope* is high. In the recent past, when the yield curve *slope* flattens, the performance of the strategy also decreases, leading to a flat cumulative return chart. This visual analysis gives a first indication for a link between the yield curve *slope* and the performance of the strategy. We analyze the impact of the yield curve shape on the performance of the strategies in more detail by regressing the strategy returns on different components of the US yield curve. To be more precise, we estimate the parameters of the following specifications:

(16) $$RS_t = \beta_0^{RS} + \beta_l^{RS} level_{t,US} + \beta_s^{RS} slope_{t,US} + \beta_c^{RS} curvature_{t,US} + \varepsilon_t,$$

(17) $$RS_t = \beta_0^{RS} + \beta_l^{RS} level_{t,US} + \varepsilon_t,$$

(18) $$RS_t = \beta_0^{RS} + \beta_s^{RS} slope_{t,US} + \varepsilon_t,$$

(19) $$RS_t = \beta_0^{RS} + \beta_c^{RS} curvature_{t,US} + \varepsilon_t,$$

where RS_t is the return of the analyzed trading strategy at time *t*. The returns are obtained from the performance of the base case using equation (5) for the return forecasting. We start with univariate regressions to filter out the most important factors. As can be seen in Table 16, the yield curve *slope* is the single most important factor to forecast the future returns of the strategy. With a t-statistic of 1.82 the *slope* parameter is significantly different from zero, but an R^2 of 0.05 indicates an only weak link between the yield curve *slope* and the strategy returns.

The effect of the yield curve components might be more pronounced for *performance trends of the strategy* as opposed to *single return forecasts*. Therefore, we regress the yield curve *slope* factors on the 6-month aggregate returns. This approach delivers higher R^2 ranging between 0.04 (*slope*) and 0.07 (*level*) for the univariate regressions. The t-statistics show a significant impact of the *level* and the *curvature* on the aggregate strategy return at the 10% level (t-statistics of -2.05 and 1.82 for *level* and *curvature*, respectively). For the yield curve *slope* the parameter is almost significant at the 10% level (t-statistic of 1.59). The regressions show that a yield curve with a higher *level* or *curvature* is linked to a lower aggregate strategy return. Another regression is performed with *level*, *slope*, and *curvature* as explaining variables to test for the stability of results. In this analysis the parameter of the *level* remains negative at -0.53 and -1.23 for the 1-month and 6-month strategy return case, respectively (for the 6-month strategy return case even significant with a t-statistic of -3.44). For the 6-month strategy returns, the parameters are also significant for the *slope* and the *curvature* of the yield curve (t-statistics of -3.44 and 2.75, respectively). The parameters of the *slope* in the 1- and 6-month regression change signs when compared to the univariate results. However, the multivariate results have to be interpreted with great care because of the high correlation among the curve components (compare Table 19).

Table 16: Impact of the Yield Curve Components on the Performance of the Base Strategy Using Forecasting Equation (5). This table contains the results obtained from regressing the returns of the standard trading strategy on yield curve components. The strategy forecasts future bond returns using specification (5) and invests according to Lehmann weights. The rolling period refers to the aggregation of the strategy returns. A value of 1 (6) indicates that the regression of strategy returns on curve components is performed with monthly (6-monthly) returns. The table gives the adjusted R^2 of the regressions.

Rolling Return Period	1	6	1	6	1	6	1	6
β_0^{RS}	0.0010	0.0009	0.0002	0.0003	0.0000	0.0004	0.0034	0.0058
	1.2517	*4.1184*	*0.2993*	*2.1600*	*0.1096*	*2.7970*	*0.6060*	*3.7048*
β_l^{RS}	-0.1438	-0.1471					-0.5332	-1.2291
	-0.5537	*-2.0521*					*-0.4242*	*-3.4421*
β_s^{RS}			0.2994	0.1343			-3.2466	-2.2208
			1.0370	*1.5921*			*-1.3407*	*-3.3764*
β_c^{RS}					2.0677	0.6581	12.4357	4.2705
					1.8204	*1.8250*	*2.3602*	*2.7482*
R^2	0.00	0.07	0.02	0.04	0.05	0.06	0.14	0.23

The above analysis is repeated with a strategy that uses a 36 month estimation window to arrive at the return forecasts of the bond returns in each country. This is a shorter time window than the 60 months used in the standard case. The advantage of this shorter estimation period is that 24 additional months of strategy performance data are obtained, which can be used to analyze the link between the strategy returns and the yield curve shape. The analysis confirms our previous results.[9] In the univariate case the R^2's are around 0.03 for all three yield curve components. For the 1-month return case the *slope* has the most significant parameter (parameter value of 1.79 with a t-statistic of 1.71). For the 6-month returns in the univariate regression all yield curve components are significant at the 5% level. The parameter for the *level* is negative (value of -0.32 with t-statistic of -4.08), while the parameter for the *slope* and *curvature* turns out positive (values of 0.30 and 0.85 with t-statistics of 3.10 and 2.28, respectively). In the multivariate case no parameter is significantly positive for the 1-month strategy returns. For the 6-month strategy returns in the multivariate case only the *level* is significant (parameter of -0.55 with a t-statistic of -2.16). The results indicate a positive link between the *slope* of the yield curve and the success of the trading strategy.

Table 17: Impact of the Yield Curve Components on the Performance of the Modified Strategy Using Forecasting Equation (12). This table contains the results obtained from regressing the returns of the Modified Cochrane/Piazzesi trading strategy on yield curve components. In the strategy the future bond returns are forecasted with specification (12) and invested with Lehmann weights. The rolling period refers to the aggregation of the strategy returns. A value of 1 (6) indicates that the regression of strategy returns on curve components is performed with monthly (6-monthly) returns. The table gives the adjusted R^2's of the regressions.

Rolling Return Period	1	6	1	6	1	6	1	6
β_0^{RS}	0.0028	0.0028	0.0002	0.0002	0.0006	0.0004	0.0004	0.0015
	4.0123	*9.4552*	*0.3658*	*0.7690*	*1.5017*	*2.5149*	*0.0709*	*0.6700*
β_l^{RS}	-0.6533	-0.6148					-0.2087	-0.2850
	-2.7849	*-6.3556*					*-0.1772*	*-0.5519*
β_s^{RS}			0.6191	0.7288			2.4347	-0.1044
			2.3189	*6.5965*			*1.0731*	*-0.1097*
β_c^{RS}					1.5970	3.1396	-8.5357	2.2647
					1.4577	*6.6095*	*-1.7292*	*1.0079*
R^2	0.11	0.41	0.08	0.43	0.03	0.43	0.17	0.44

We modify the standard strategy by using the modified Cochrane/Piazzesi approach (i.e., forecasting specification (12) is used) with a 60-month standard estimation period and Lehmann weights (compare Table 17). For the 1-month strategy returns and univariate regressions the *level* delivers the highest explanatory power (R^2 of 0.11). The parameter of the *level* is -0.65 and significantly different from zero (t-statistic of -2.78). For the

[9] Results are not summarized in tables for brevity.

slope a positive parameter of 0.62 is obtained which is significant at the 1% level (t-statistic of 2.32). This indicates that a higher *slope* is associated with a higher strategy return. The *curvature* has a positive parameter of 1.60, which is not significantly different from zero (t-statistic of 1.46). For the rolling 6-month returns, the highest explanatory power is obtained for the *slope* and *curvature* of the yield curve (R^2 of 0.43). The parameter of the *slope* remains significantly positive (parameter of 0.73 with a t-statistic of 6.60), while the parameter of the *curvature* stays positive, but becomes also significantly different from zero (value of 3.14 with a t-statistic of 6.61). For the *level* as dependent variable an R^2 of 0.41 is obtained. The obtained parameter is significantly negative (parameter of -0.62 with a t-statistic of -6.36). For the multivariate regression R^2's of 0.17 and 0.44 are obtained for the 1-month and 6-month return horizon, respectively. The results of the multivariate specification are not very stable though, which might be attributable to the high correlation among the explaining variables. Notable is that the parameter of the *slope* and *curvature* change signs for the 6- and 1-month case, respectively (*slope* parameter changes from 0.73 to -0.10 for the 1-month case, while the parameter of the *curvature* changes from 1.60 to -8.54 for the 6-month strategy return case). However, none of these changes occurs for parameters which are significantly different from zero.

In summary, there appears to be evidence for the impact of the yield curve components on the performance of the trading strategies. The R^2's and the t-statistics indicate that the level of the yield curve has the strongest impact on the performance of the strategy. A lower level is found to be linked to a higher return of the strategy. Because of the high correlation among *level*, *slope*, and *curvature* (absolute values are above 0.75), the results of the multivariate case have to be considered with care and the effects of the different yield curve components on the strategy returns are difficult to separate from each other.

9. Panel Regression of Strategy Performance in Each Country on the National Yield Curve Components

In this section a panel regression is performed to analyze the link between the yield curve components and the performance of the strategies more closely. The advantage of a panel regression is that we can analyze the systematic links between the performance of a strategy in a country and its national yield curve components directly. This allows us to measure the performance impact of the different yield curve components in a more precise way. This approach eliminates noise in the previous regression analysis caused by regressing the performance of the international strategy on the characteristics of the US yield curve. The panel regressions are performed with panel-corrected standard errors (PCSE) as introduced by Beck and Katz (1995). The PCSE correct for contemporaneous correlation and heteroscedasticity among the returns in the different countries as well as for autocorrelation within the returns of each country. The performance of the strategy in each country is determined by going long the bonds of the country if the forecasted return is positive and short otherwise (compare Section 7).

Table 18: Impact of the Yield Curve on the Performance of the Modified Strategy Using Forecasting Equation (12) and a Panel Regression. This table contains the results of a panel regression of the performance of the strategy in each country on the components of the respective national yield curve. The performance of the strategy in each country is obtained by going long if the forecasted returns are positive and short if the forecasted returns are negative. The returns in each country and period are forecasted by using specification (12). The rolling period refers to the aggregation of the strategy returns. A value of 1 (6) indicates that the regression is performed with monthly (6-monthly) returns. The table gives the adjusted R^2 's of the regressions.

Rolling Return Period	1	6	1	6	1	6	1	6
β_0^{RS}	0.0017	0.0142	-0.0008	0.0025	-0.0004	0.0062	-0.0036	-0.0209
	3.0049	*7.3167*	*-1.5100*	*1.6627*	*-0.8140*	*4.6659*	*-2.6153*	*-4.5701*
β_l^{RS}	-0.2681	-1.8725					0.7996	5.7847
	-1.4598	*-3.2843*					*2.4074*	*5.3953*
β_s^{RS}			2.0629	9.9662			2.3614	25.4990
			4.4290	*6.8748*			*2.0037*	*7.2964*
β_c^{RS}					10.9493	38.7462	5.8024	-31.5014
					4.8646	*5.2523*	*1.3896*	*-2.5536*
R^2	0.00	0.03	0.06	0.14	0.08	0.09	0.09	0.19

Using standard specification (5) to forecast returns, a very low explanatory power is obtained for most specifications. The R^2 's are only for the 6-month rolling returns above 0.02.[10] This weak link between strategy performance and yield curve characteristics might be partially motivated by the erratic performance of the strategy in the different countries (e.g., as can be seen in Table 15 the strategy works well in the US, but not so well in Germany). Using specification (12) (i.e., the Modified Cochrane/Piazzesi approach) to forecast returns and investing accordingly delivers more consistent profits across countries (compare Table 15). Therefore, we invest according to the forecasts of specification (12) in each country and panel-regress the resulting national strategy returns on the characteristics of the respective national yield curve. As can be seen in Table 18, the results improve drastically. The highest R^2 is obtained for the *curvature* of the yield curve (value of 0.08). The estimated parameter is 10.95 (t-statistic of 4.86), indicating a positive link between the performance of the strategy and the *curvature* of the yield curve. The R^2 for the univariate regression of 1-month returns on the *slope* reaches 0.06. The *slope* parameter is 2.06 and has a t-statistic of 4.43. The link between the strategy performance in a country and the country's yield curve *slope* appears to be relatively strong. For the 6-month returns all the yield curve components are significantly different from zero in the panel regression (t-statistics of at least -3.28). The parameter estimates of the *slope* and the *curvature* are positive (9.97 and 38.75, respectively), while the *level* has a negative parameter (value of-1.87). In the multivariate panel regression using 1-month strategy returns, the *level* and *slope* are the only significant factors with parameters of

[10] Results not reported here for brevity.

0.80 and 2.36, respectively (t-statistic of 2.41 and 2.00). For the 6-month strategy returns all yield curve factors are significant. The *curvature* of the yield curve changes the sign as compared to the univariate case (from 38.75 to -31.50).

The results in Sections 8 and 9 show that the positive link of the *slope* of the yield curve and the strategy performance is robust in time series as well as panel regressions. Even in the multivariate case of the panel regression the results for the slope are robust (i.e., the parameters do not change signs). For the univariate cases of the *level* and *curvature* as explaining factor the results in this section and Section 8 are consistent. Sign changes are only observed in the difficult-to-interpret multivariate cases. These analyses find that the performance of the strategies is stronger when the short term interest rates are lower, the yield curve is steeper or the curvature is higher. In other words, the forecasting power of the forward curve depends on the shape of the yield curve. However, the R^2 's are moderate and there appear to be other important factors with significant influence on the strategy performance. Furthermore, the high correlations between *level*, *slope*, and *curvature* make it difficult to isolate the effect of the respective yield curve component on the fund performance. Unfortunately our data covers a time frame of only ten years and the power of this analysis has its limitations.

10. Bayesian Model Averaging

Its is well known that searching for the best specification (for a given set of variables) will expose the researcher to inflated t-values and little guidance for choosing between models with almost equal likelihood. In other words there is significant model uncertainty. One of the methods suggested in the literature has been Bayesian Model averaging. Suppose there is a set of $i = 1,...,k,...,q$ models M_i .For every moment in time we calculate the posterior probability that model k is the correct model, $p(M_k|data)$.

(20) $$p(M_k|data) = \frac{p(data|M_k)\,p(M_k)}{\sum_i p(data|M_i)\,p(M_i)}$$

where $p(data|M_k)$ is the probability of the data given that M_k is the correct model and $p(M_k)$ is the prior probability for model k. Assuming that $p(M_i) = \frac{1}{q}$ we can rewrite (20) as

$$p(M_k|data) = \frac{p(data|M_k)}{\sum_i p(data|M_i)} = \frac{1}{\sum_i B_{ik}}$$

where the Bayes-factor, B_{ik} can be approximated by the so called BIC approximation[11]

(21) $$B_{ik} \approx \exp\left(\frac{BIC_k - BIC_i}{2}\right)$$

As the BIC value is readily available regression output for most software packages this allows us to calculate (20) without much computational effort.

Indexing an individual country by j we get at any point in time an $n \times 1$ vector assigning probabilities to each of the q regression models, $\mathbf{P}_{j,t}$ as well as a $n \times (m+1)$ matrix of OLS regression coefficients (m regressors plus one constant), $\mathbf{\Theta}_{j,t}$. Combined with our

[11] See Raftery (1994) for further reference and relevant S-Plus code.

knowledge of forward rates at time t, represented by $\mathbf{F}_{j,t}$ we can now generate a forecast for country j

(22) $$\widehat{RX}^{bma}_{t+1,j} = \sum_{i=1}^{q} p_t\left(M_{i,j}\,|\,data\right) E_t\left(\widehat{RX}_{t+1,j}\,|\,M_{i,j}\right) = \mathbf{P}^T_{t,j}\mathbf{\Theta}_{t,j}\begin{bmatrix}1\\ \mathbf{F}_{t,j}\end{bmatrix}$$

These forecasts are now taken as inputs into our portfolio construction rules. We can now compare our previous approach (use a specification that seems intuitive and worked well) with Bayesian model averaging. The results are summarized in Figure 4.

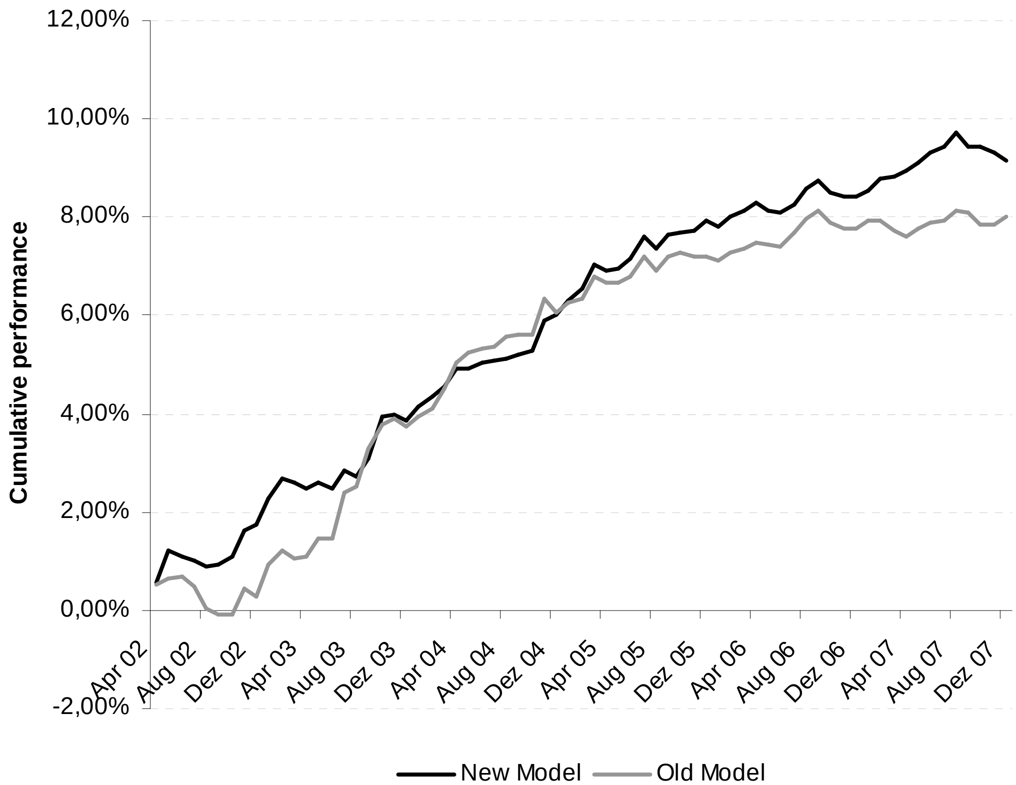


Figure 4. Classical forecasts (old model) versus Bayesian model averaging. Bayesian model averaging provides superior strategy returns by delivering a higher information ratio and less variable performance across different time periods.

Bayesian model averaging achieves a higher and smoother performance. It also avoids the flattening out of the strategy (during the last 12 month). Combining forecasts by weighting them with the respective model probability remains to be an attractive strategy.

11. Conclusion

This article illustrates that the model introduced by Cochrane and Piazzesi (2005) can be used to develop profitable trading strategies. While Cochrane and Piazzesi (2005) use their model in the US market, we are the first to test its application in international fixed income markets. Their model is stable in a range of different market environments across the globe. Unlike Cochrane and Piazzesi (2005), our strategies deliver the best results when implemented with a relatively short forecasting horizon of 1 month. An alternative forecasting specification developed in this article also delivers a high forecasting power for international fixed income returns. We arrive at strategies with an information ratio in excess of 1.5. The performance of the trading strategies is found to be influenced by the shape of the yield curve. Therefore, the extend of the information stored in the forward curve appears to be depending on the shape of the yield curve.

APPENDIX

Table 19: Correlations of Explaining Variables. This table contains the correlations between the forward rates used in the Cochrane / Piazzesi Model for all countries in the chosen universe.

AUS	$F^{0\to1}$	$F^{1\to2}$	$F^{2\to3}$	$F^{3\to4}$	$F^{4\to5}$
$F^{0\to1}$	1.00	0.77	0.66	0.57	0.45
$F^{1\to2}$	0.77	1.00	0.97	0.94	0.88
$F^{2\to3}$	0.66	0.97	1.00	0.99	0.95
$F^{3\to4}$	0.57	0.94	0.99	1.00	0.98
$F^{4\to5}$	0.45	0.88	0.95	0.98	1.00

CAN	$F^{0\to1}$	$F^{1\to2}$	$F^{2\to3}$	$F^{3\to4}$	$F^{4\to5}$
$F^{0\to1}$	1.00	0.94	0.78	0.68	0.56
$F^{1\to2}$	0.94	1.00	0.88	0.81	0.71
$F^{2\to3}$	0.78	0.88	1.00	0.97	0.91
$F^{3\to4}$	0.68	0.81	0.97	1.00	0.98
$F^{4\to5}$	0.56	0.71	0.91	0.98	1.00

GER	$F^{0\to1}$	$F^{1\to2}$	$F^{2\to3}$	$F^{3\to4}$	$F^{4\to5}$
$F^{0\to1}$	1.00	0.93	0.85	0.78	0.72
$F^{1\to2}$	0.93	1.00	0.97	0.89	0.84

$F^{2\to3}$	0.85	0.97	1.00	0.95	0.94
$F^{3\to4}$	0.78	0.89	0.95	1.00	0.97
$F^{4\to5}$	0.72	0.84	0.94	0.97	1.00

JAP	$F^{0\to1}$	$F^{1\to2}$	$F^{2\to3}$	$F^{3\to4}$	$F^{4\to5}$
$F^{0\to1}$	1.00	0.83	0.73	0.50	0.64
$F^{1\to2}$	0.83	1.00	0.89	0.72	0.83
$F^{2\to3}$	0.73	0.89	1.00	0.90	0.93
$F^{3\to4}$	0.50	0.72	0.90	1.00	0.90
$F^{4\to5}$	0.64	0.83	0.93	0.90	1.00

CH	$F^{0\to1}$	$F^{1\to2}$	$F^{2\to3}$	$F^{3\to4}$	$F^{4\to5}$
$F^{0\to1}$	1.00	0.94	0.87	0.79	0.70
$F^{1\to2}$	0.94	1.00	0.95	0.89	0.81
$F^{2\to3}$	0.87	0.95	1.00	0.92	0.85
$F^{3\to4}$	0.79	0.89	0.92	1.00	0.96
$F^{4\to5}$	0.70	0.81	0.85	0.96	1.00

UK	$F^{0\to1}$	$F^{1\to2}$	$F^{2\to3}$	$F^{3\to4}$	$F^{4\to5}$
$F^{0\to1}$	1.00	0.91	0.83	0.82	0.81
$F^{1\to2}$	0.91	1.00	0.98	0.96	0.93
$F^{2\to3}$	0.83	0.98	1.00	0.99	0.96
$F^{3\to4}$	0.82	0.96	0.99	1.00	0.98
$F^{4\to5}$	0.81	0.93	0.96	0.98	1.00

USA	$F^{0\to1}$	$F^{1\to2}$	$F^{2\to3}$	$F^{3\to4}$	$F^{4\to5}$
$F^{0\to1}$	1.00	0.95	0.86	0.76	0.69
$F^{1\to2}$	0.95	1.00	0.96	0.87	0.83
$F^{2\to3}$	0.86	0.96	1.00	0.94	0.94
$F^{3\to4}$	0.76	0.87	0.94	1.00	0.95
$F^{4\to5}$	0.69	0.83	0.94	0.95	1.00

Table 20: Correlation of the Restricted Cochrane / Piazzesi (2005) Factor and the Level, Slope, and Curvature of the Yield Curve. This table contains the correlations between the *level*, *slope*, *curvature*, and the restricted Cochrane / Piazzesi factor for all the countries in the sample.

AUS	Γ	*level*	*slope*	*curve*
Γ	1.00	0.40	-0.03	0.06
level	0.40	1.00	-0.74	-0.50
slope	-0.03	-0.74	1.00	0.90
curve	0.06	-0.50	0.90	1.00

CAN	Γ	*level*	*slope*	*curve*
Γ	1.00	0.11	0.33	0.51
level	0.11	1.00	-0.80	-0.51
slope	0.33	-0.80	1.00	0.88
curve	0.51	-0.51	0.88	1.00

GER	Γ	*level*	*slope*	*curve*
Γ	1.00	0.39	0.39	0.30
level	0.39	1.00	-0.50	-0.26
slope	0.39	-0.50	1.00	0.79
curve	0.30	-0.26	0.79	1.00

JAP	Γ	*level*	*slope*	*curve*
Γ	1.00	0.63	0.49	0.27
level	0.63	1.00	0.00	0.34
slope	0.49	0.00	1.00	0.60
curve	0.27	0.34	0.60	1.00

CH	Γ	*level*	*slope*	*curve*
Γ	1.00	0.04	0.50	0.39
level	0.04	1.00	-0.78	-0.66
slope	0.50	-0.78	1.00	0.78
curve	0.39	-0.66	0.78	1.00

UK	Γ	*level*	*slope*	*curve*
Γ	1.00	0.55	0.00	0.00
level	0.55	1.00	-0.74	-0.47
slope	0.00	-0.74	1.00	0.75
curve	0.00	-0.47	0.75	1.00

USA	Γ	*level*	*slope*	*curve*
Γ	1.00	-0.06	0.39	0.56
level	-0.06	1.00	-0.90	-0.79
slope	0.39	-0.90	1.00	0.95
curve	0.56	-0.79	0.95	1.00

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