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Varying risk premia in international bond markets ☆

Stephan Kessler, Bernd Scherer *

Morgan Stanley Investment Management, 25 Cabot Square, London E14 4QA, UK

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ABSTRACT

Cochrane and Piazzesi [Cochrane, J.H., Piazzesi, M., 2005. Bond risk premia. American Economic Review 95, 138–160] 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. Furthermore, we cannot 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 and outperform alternative approaches. We introduce an alternative specification to forecast future bond returns and achieve superior risk-adjusted returns in our trading strategy. Bayesian model averaging is used to enhance the performance of the proposed trading strategy.

1. Introduction

This article gives an introduction and thorough test of a new fixed income trading strategy. The trading strategy uses an international modification of the Cochrane and Piazzesi (2005) model to generate monthly bond return forecasts. The usage of the model by Cochrane and Piazzesi (2005) is motivated by its good forecasting ability for the US bond market. Furthermore, it has never been thoroughly tested as a driver for fixed income trading strategies.

The return forecasts are generated for major global fixed income markets. Using rolling windows to fit the model, our results are not subject to an in-sample forecasting bias. The trading strategy is implemented by constructing portfolios which go long in fixed income markets with relatively positive forecasts and short in fixed income markets with relatively negative forecasts. Per construction the long and short positions of the strategy sum to zero and, thus, the trading strategy is self-financing. The Cochrane and Piazzesi (2005) specification proves to be a good specification to drive the strategy.

The usage of different portfolio construction methodologies and parameter settings prove the stability of our results. We introduce a modified forecasting specification which exploits the forecasting ability of the US market for other financial markets. This modified specification performs particularly well. In our setting there are many possible specifications to forecast bond returns and there is no clear theoretical guidance to choose one of them. Thus, a Bayesian model averaging (BMA) framework is introduced to determine the return forecast as a weighted average across different forecasting models. Running an investment strategy with a BMA forecast proves to deliver the highest performing strategy with information ratios in excess of one. Finally, the performance of the trading strategy is benchmarked against an alternative strategy using short rate momentum, the yield curve slope, and the real yield as forecasting variables. These variables are used in a similar study by Ilmanen (1997). Another benchmark is established by comparing the results of our approach with a trading strategy which uses the yield curve model by Diebold and Li (2006) to forecast bond returns. However, the trading strategy advocated in this article clearly outperforms both benchmarks.

Cochrane and Piazzesi (2005) focus on the US fixed income market. Before applying their results to other fixed income markets we need to test whether their approach is applicable on an international level. Thus, as a by-product of our analysis, we contribute to the existing literature by conducting a thorough analysis on the extension of the Cochrane and Piazzesi (2005) results to other international financial markets. Our analyses find that their approach works well for all major global fixed income markets and serves as a stability test. The fit of the forecasting regressions for

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* Corresponding author. Tel.: +44 207 425 4016; fax: +44 207 056 5748.
E-mail addresses: stephan.kessler@morganstanley.com (S. Kessler), bernd.scherer@morganstanley.com (B. Scherer).

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other countries is comparable to the one found for the US. For 1-year return forecasts R^2's are on average 0.56. In contrast to Cochrane and Piazzesi (2005) there is no evidence for a tent shape of the forecasting parameters.[1]

There is a large range of literature linked to our research which we do not want to neglect. The previous literature around the forecasting of bond returns can be classified in two broad categories. Articles in the first category start with a forecast of the yield curve for a certain point in time in the future. This yield curve forecast is used to discount the remaining cash flows of a bond at this point in time, effectively predicting the bond price. Comparing the market price of a bond today with its predicted price gives a bond return forecast. Diebold and Li (2006), Diebold et al. (2006), Diebold et al. (2007) and Ang and Piazzesi (2003) follow this approach. Articles in the second category do not take the detour via the yield curve forecast, but predict bond returns directly. Often such a bond return forecast is obtained by regressing bond returns on lagged economic variables and using the estimated parameters to forecast.[2]

Ilmanen (1995), Kim and Moon (2005) and Ludvigson and Ng (2005) successfully predict fixed income returns in a regression approach with a range of macroeconomic variables. Fama and Bliss (1987), Stambaugh (1988), and Cochrane and Piazzesi (2005) predict future bond returns using the forward curve. Our research follows the latter approach and adds international evidence to previous work.

Analyses of fixed income trading strategies form another strand of research closely linked to our article. Fixed income trading strategies in their classic form exploit features of the yield curve. Chua et al. (2006) and Bieri and Chincarini (2005) play different points on the yield curve against each other in simultaneous trades.[3]

Duarte et al. (2005) also analyze such yield curve based strategies but extend their article to swap spread arbitrage, mortgage arbitrage, volatility arbitrage, and capital structure arbitrage. However, the strategy we apply is more similar to Ilmanen (1997) who uses bond excess return forecasts. In contrast to this article, we do not apply economic factors but restrict ourselves to a forecast using forward rates. Appendix of Cochrane and Piazzesi (2005) hints at such an application of their model for a successful trading strategy. Results by Kotomin et al. (2008) on seasonality in bond spreads can be used for fixed income trading strategies.

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. Bayesian model averaging is used in Section 8 to obtain a more stable strategy performance. Section 9 studies the link between the shape of the yield curve and the performance of our trading strategies. In Section 10 the strategy is compared with a range of other fixed income trading strategies. The conclusions are given in Section 11.

2. Methodology

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

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

The forward rate at time t for a 12 month loan between $t + i - 12$ and $t + i$ is expressed and calculated as

$$F_t^{(i-12)\to i} = \ln(P_t^i) - \ln(P_t^{(i-12)}). \tag{2}$$

For $i = 12$ Eq. (2) becomes the 1-year spot rate. The bond return in excess of the risk free rate, c_t, is given by

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

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

$$\overline{RX}_t^{12N} = \frac{1}{N}\sum_{n=1}^{N} RX_t^{12n}, \tag{4}$$

where we introduce the auxiliary index n to make the bond maturities in the sum of Eq. (4) run across 12 month time spacings and set $N = 5$ (i.e., we focus on the shorter end of the yield curve using a set of tenors ranging from 12 to 60 months in equal 12 month steps).[4] Cochrane and Piazzesi (2005) expressed future bond returns as a linear regression of realized excess returns versus 1-month lagged forward rates:

$$RX_{t+1}^u = \gamma_o + \sum_{n=1}^{N} \gamma_n F_t^{(12n-12)\to 12n} + \varepsilon_{t+1}, \tag{5}$$

with $\varepsilon_{t+1} \sim N(0, \sigma)$. This specification is used to forecast future excess returns $\widehat{RX}_{t+1}^n$. We also run regressions with the average period return as dependent variable, i.e.,

$$\overline{RX}_{t+1}^N = \gamma_o + \sum_{n=1}^{N} \gamma_n F_t^{(12n-12)\to 12n} + \varepsilon_{t+1} = \gamma_o + \gamma^T f_t + \varepsilon_{t+1}, \tag{6}$$

where $f_t = [F_t^{0\to 12}, F_t^{12\to 24}, \ldots, F_t^{48\to 60}]^T$. 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 run a restricted version of (5). The parameters of this specification are estimated from

$$RX_{t+1}^u = \gamma_o + \eta \Gamma_t + \zeta_{t+1}. \tag{7}$$

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, $\widehat{RX}_{t+1}^u$, with forward rates known at time t, we employ various portfolio construction methodologies. Our first approach is to use Leh-

[1] Cochrane and Piazzesi (2005) find the following pattern for the parameters of the five forward rates in their regression: Parameter 1 < Parameter 2 < Parameter 3 and Parameter 3 > Parameter 4 > Parameter 5. This pattern is robust in a range of stability tests and appears to be a feature of the US fixed income market.

[2] Compare Nam et al. (2005) for a recent study using regression forecasting in the equities space.

[3] A very basic and simplified approach to such a strategy is a carry trade between 2 and 10 year zero couponbonds. As the duration of zero bonds is equal to their time to maturity, a duration neutral portfolio can beconstructed by going long 5 bonds with 2 years to maturity and going short 1 bond with 10 years to maturity. Such a portfolio would earn 5 times the yield on the 2 year bonds and once the yield on the 10 year bond. Unless the yield curve is very steep or there are massive changes in the yield curve during the holding period, such a position should earn a positive return. Refer to Chua et al. (2006) and Bieri and Chincarini (2005) for a more detailed and precise discussion.

[4] The relationship between the auxiliary index n and our superscripts u for the bond maturity as well as i for the forward rates can be expressed as $u = 12n$ and $i = 12n$, respectively.

mann weighting, i.e., we set the portfolio weight of each bond equal to its forecasted return.[5]

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 $j = 1, \ldots, C$ is given by

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

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.

Since we analyze a range of different trading strategies in this article, we need to ensure that they are comparable. This is facilitated by scaling them to the same ex ante risk level. We set an ex ante target return volatility of 1% per annum for all strategies and choose the aggressiveness factor Ψ_t for each strategy at each time t accordingly.[6]

To come up with the right aggressiveness factor, we apply the following procedure. As a starting point we use an auxiliary aggressiveness factor of $\Psi_t = 1$ and the return forecasts $\widehat{RX}_{t+1}^{u,ALL} = [\widehat{RX}_{t+1,1}^{u}, \ldots, \widehat{RX}_{t+1,C}^{u}]$ for all C countries in Eq. (8). We term the resulting weights vector w_t^1. The annualized ex ante return volatility, $\sigma_S(w_t^1)$, of this portfolio can be determined as

$$\sigma_S(w_t^1) = \sqrt{12 \cdot w_t^{1\prime} \Omega_t w_t^1}, \tag{9}$$

where Ω_t is the monthly return covariance matrix of the bond returns. Given our ex ante target risk level of 1% per annum, we can now determine the required aggressiveness factor Ψ_t at time t for our analysis:

$$\Psi_t = \frac{1}{100 \cdot \sigma_S(w_t^1)}. \tag{10}$$

The second portfolio construction approach is to build wing portfolios by equally over and underweighting bond markets with high (low) expected performance. To implement this idea, we use forecasted bond returns $\widehat{RX}_{t+1}^{u,ALL} = [\widehat{RX}_{t+1,1}^{u}, \ldots, \widehat{RX}_{t+1,C}^{u}]$ for all countries in our sample and rank them from lowest to highest. Thus, we assign a rank of 1 to the smallest element of $\widehat{RX}_{t+1}^{u,ALL}$ and a rank of C to the largest element. Then we can determine the weights in country j as

$$w_{t,j}^{wing} = \Lambda_t \begin{cases} +1 & \rho(\widehat{RX}_{t+1,j}^{u}) > C - W, \\ -1 & \rho(\widehat{RX}_{t+1,j}^{u}) \leq C, \end{cases} \tag{11}$$

where $\rho(\widehat{RX}_{t+1,j}^{u})$ is the rank assigned to the forecasted return at $t+1$ in country j and Λ_t is a (different) aggressiveness factor. 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. For comparability reasons across specifications, we choose Λ_t to target an ex ante annual return volatility of 1%. For example, in a universe with $C = 7$ countries and a chosen wing size of $W = 3$, Eq. (11) will go long 100% in each of the three countries with the highest return forecast and short – 100% in each of the three countries with the lowest return forecast. In this example, the country with the return forecast equal to the median of $\widehat{RX}_{t+1}^{u,ALL}$ will have a weight of zero. Using the same approach described in Eqs. (9) and (10) for Lehmann weights, the aggressiveness factor Λ_t is then chosen to scale the portfolio weights to an ex ante volatility of 1% per annum.

In this article, we decide to apply Lehmann weighted and equally weighted cash-neutral portfolios. The choice of these two approaches is motivated by our emphasis on return forecasts. Weights are determined in an easy and intuitive approach without interference from other estimated inputs. This allows a more precise attribution of differences in performance to alterations of the forecasting procedure. The relative advantage of the two approaches depends on the quality of a signal. If a signal is very precise, Lehmann weights can improve performance by giving the highest weight to the asset with the best forecast and the lowest weight to the asset with the worst forecast. If a forecast is noisy, it is often better to just take equally weighted long (short) positions in assets with particularly positive (negative) forecasts as the highest (lowest) return might not necessarily be realized for the asset with the highest (lowest) forecast. Our approaches are used in a range of articles with a focus on trading strategies, among others in Ilmanen and Sayood (2002), Cooper et al. (2001) and Wang and Yu (2004). In contrast, a determination of investment weights with a classical Markowitz type portfolio optimization would include an estimation of the covariance matrix. In that case, our results would also be subject to estimation errors in the covariance matrix and a comparison of forecasting methodologies might be more difficult. In addition, portfolio optimization is often found to return unstable results and corner solutions (compare, among others, Scherer and Martin (2005)).

For the performance evaluation we calculate the mean returns μ and the volatility σ of the monthly returns of our strategy. These figures are used to calculate the t-statistic of the mean returns as

$$t\text{-value} = \frac{\mu}{\sigma} \cdot \sqrt{T}, \tag{12}$$

where T is the total number of periods in the sample. For a risk-adjusted measurement of the strategy performance we calculate the information ratio. As the chosen strategy is cash-neutral and no benchmark is readily available[7], we define the information ratio for the annual strategy performance as

$$IR = \frac{\mu}{\sigma} \cdot \sqrt{12}. \tag{13}$$

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

$$TO_t = \sum_{j=1}^{C} |w_{t,j} - w_{t-1,j}|. \tag{14}$$

Average turnover is calculated as $\overline{TO} = \frac{1}{T}\sum_{t=1}^{T} TO_t$.

3. Data

The article studies the forecasting power of forward rates for future zero coupon bond excess returns in seven 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

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

[6] There is no particular reason to choose an ex ante risk level of 1% per annum. The only important step is to choose the same ex ante risk level for all strategies to make the mean returns and the portfolio turnover figures comparable.

[7] Compare Grinold and Kahn (2000) for further information. For long only investments with a declared benchmark, the information ratio is defined as the average idiosyncratic excess return component of an investment divided by the volatility of the idiosyncratic excess returns. For cash-neutral investment strategies, the IR is commonly calculated as the ratio of average returns and return volatility.

Table 1
International forecasting power of the Cochrane and Piazzesi (2005) specification (12-month forecast).

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

Note: We use Eq. (5), where the dependent variable is the 12 month bond return on a 5 year zero bond. The numbers below the parameter values denote the respective *t*-values. In this table the results for Australia (AUS), Canada (CAN), Germany (GER), Japan (JAP), Switzerland (CH), United Kingdom (UK), and the United States (USA) are summarized. Parameters significant at the 95% confidence level are printed in bold.

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 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 1–4 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 2007. This is the longest possible time frame for which yield curve data for all countries in the sample is available to us.

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^2s of around 0.35. Using the unrestricted specification (5) for $u = 60$, i.e., on 5 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^2s between 0.38 for Switzerland and 0.69 for Canada. This is hardly surprising since we have used overlapping data.

The parameter on $F_t^{0\to12}$ (1-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 5 year bonds if the short-term yield is higher. For $F_t^{12\to24}$ (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 $F_t^{24\to36}$ and $F_t^{36\to48}$ 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 $F_t^{48\to60}$ 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 $F_t^{48\to60}$ rates are an indicator for higher returns of zero bonds with a maturity of 5 years.

Cochrane and Piazzesi (2005) report that the estimated parameters for the USA exhibit a tent shape. Using US data from 1964 to 2001, Bansal et al. (2004) confirm a tent shape of the parameters when using forward rates to forecast bond returns. Similar results are also found by Stambaugh (1988). In our analysis we do not find strong evidence for such a tent shape in the USA in the analyzed time frame.[8]

The parameter estimated for the US $F_t^{0\to12}$ is larger than the one estimated for $F_t^{12\to24}$ (compare Table 1). In fact, for the 12 month return forecasts, we do not find any systematic pattern across the countries in our universe. The only country which exhibits a pattern similar to the one found in Cochrane and Piazzesi (2005) is Germany. The parameters estimated for Germany increase from $\gamma_1 = -46.18$ to $\gamma_4 = 54.75$ and decrease to $\gamma_5 = -28.58$. However, unlike Cochrane and Piazzesi (2005), the largest estimated parameter is γ_4 and not γ_3. We also analyze the parameters of zero bonds with 1–4 years of maturity, but cannot find a tent shape pattern either. This gives evidence that the results of Cochrane and Piazzesi (2005) with respect to the tent shape of the estimated parameters are not easily 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.

Although there is no clear pattern in the parameters, the R^2s indicate a strong link between the forward curve and the bond returns. Given the high explanatory power, the missing pattern might be caused by the estimation difficulties arising out of the high correlations between the explaining variables. The correlations of the explaining variables are higher than 0.4 for all factors and all countries.[9]

[8] To test for the stability of this result we analyze subsets of our data and do not find the tent shape either. Furthermore, the Fama and Bliss (1987) data is used to rerun the results for the US with the same data used by Cochrane and Piazzesi (2005). For the time frame we study, our results are confirmed and no pattern is found. However, using the Fama and Bliss (1987) data on the same time frame used by Cochrane and Piazzesi (2005) we can confirm the tent shape. Thus, it appears that the tent shape is a result which applies to certain observation periods, but is not a consistent pattern found in arbitrary time frames. Readers comparing our results with Cochrane and Piazzesi (2005) might notice that our estimated parameters have a larger magnitude. This can be explained by the fact that we quote our forward rates on a monthly basis and Cochrane and Piazzesi (2005) on a yearly basis. Thus, the absolute values of our estimated parameters are larger by a constant factor of 12. However, this is only a quotation convention and the research approach as well as the results are equivalent.

[9] For details on correlations please refer to the Appendix.

Table 2
International forecasting power of the Cochrane and Piazzesi (2005) specification (1-month forecast).

Parameter	AUS	CAN	GER	JAP	CH	UK	USA
γ_0	−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

Note: We use Eq. (5), where the dependent variable is the 1-month bond return on a 5 year zero bond. The numbers below the parameter values denote the respective t-values. In this table the results for Australia (AUS), Canada (CAN), Germany (GER), Japan (JAP), Switzerland (CH), United Kingdom (UK), and the United States (USA) are summarized. Parameters significant at the 95% confidence level are printed in bold.

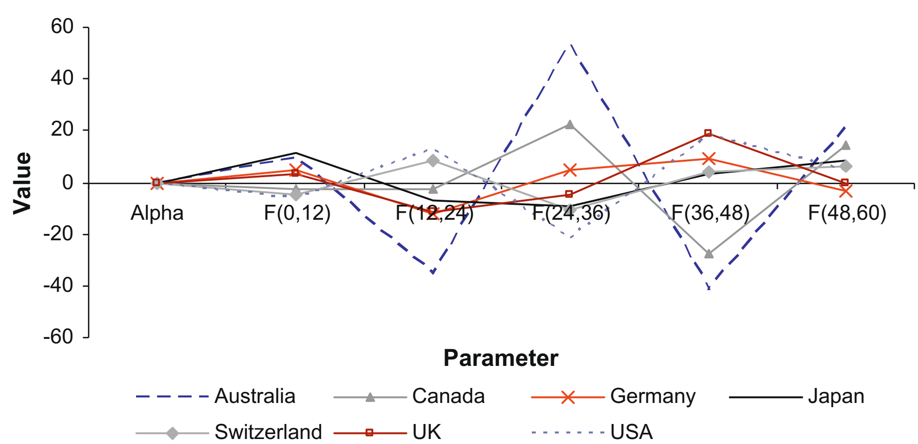

Fig. 1. Parameter estimates for the standard model and a 1-month forecasting horizon. *Note:* This graph depicts the parameter estimates for the standard forecasting model using specification (5). The forecasting horizon is 1-month. The term $F(a,b)$ stands for $F^{a\to b}$. Alpha measures the intercept of the regression.

Table 3
International forecasting power of the restricted Cochrane and Piazzesi (2005) specification in (7).

Parameter	AUS	CAN	GER	JAP	CH	UK	USA
γ_0	**−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

Note: The dependent variable is the 12 month excess bond return of a bond with 5 years to maturity and the independent variable is the restricted factor Γ. The numbers below the parameter values denote the respective t-values. In this table the results for Australia (AUS), Canada (CAN), Germany (GER), Japan (JAP), Switzerland (CH), United Kingdom (UK), and the United States (USA) are summarized. Parameters significant at the 95% confidence level are printed in bold.

For the UK the correlations are particularly high, ranging between 0.81 for $\rho(F_t^{0\to 12}, F_t^{48\to 60})$ and 0.98 for $\rho(F_t^{36\to 48}, F_t^{48\to 60})$. Even, if there were 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. In short, specification (5) appears problematic from an econometric point of view.

As can be seen in Table 2, the forecasting power of the forward curve for the bond returns 1-month ahead is much lower (R^2s 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 Fig. 1).

When forecasting with the restricted model of Eq. (7), similar results are obtained.[10]

[10] 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.

Table 4
International forecasting power of the Restricted Cochrane and Piazzesi (2005) specification in (7).

Parameter	AUS	CAN	GER	JAP	CH	UK	USA
γ_0	**−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

Note: The dependent variable is the 1-month excess bond return and the independent variable is the restricted factor Γ. The numbers below the parameter values denote the respective t-values. In this table the results for Australia (AUS), Canada (CAN), Germany (GER), Japan (JAP), Switzerland (CH), United Kingdom (UK), and the United States (USA) are summarized. Parameters significant at the 95% confidence level are printed in bold.

For a forecasting horizon of 12 months, the R^2s range between 0.38 for Switzerland and 0.66 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 above 8 for all countries. The parameter is for all countries in a range between 8 and 14, which indicates that the effect of the systematic factor on future bond returns is similar across all countries in the sample.

Once a forecasting horizon of 1-month is chosen, the forecasting power is reduced. The results are given in Table 4. We arrive at R^2s 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 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) in an international context.[11]

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

In this section we move from investigating statistical significance to economic significance. Using the standard specification in Eq. (5), we test various trading strategies.[12]

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 months) as well as the choice of universe. In some of our analyses we exclude Japan from the investment universe. This step is motivated by the fact that Japanese interest rates are very low for a considerable time frame and the term spread is comparably low. Thus, the Japanese yield curve has a different structure than in other countries and this might have an impact on the findings. Our results are summarized in Table 5. The strategy with a 60 month estimation window and Lehmann weights on the full universe is our *base case*.

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 information ratios we achieve reflect a reasonably strong performance. Information ratios found in comparable research are usually between 0.7 and 1.5 (Conover et al., 2007; Alexander and Dimitriu, 2002; Panigirtzoglou, 2007). 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.[13]

The choice of Lehmann weights is uncritical for the performance of the strategies. In fact, choosing equally weighted portfolios 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. Using the whole range of countries and a wing size of three the information ratio (*IR* of 0.78) is higher than for the respective case with Lehmann weighting (*IR* of 0.74). For the strategy without Japan the results are mixed, but for a wing size of two and three we obtain an increase in performance (*IR* of 1.01 and 1.05, respectively, compared to 0.90 for the Lehmann weights). The more robust equal weighting approach appears bet-

[11] 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 on 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 in economic profitability. Compare Beechey et al. (2009) for a discussion of cointegration in interest rates.

[12] Appendix B of Cochrane and Piazzesi (2005) touches shortly on this topic and finds some evidence that there might be a successful trading strategy.

[13] 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. 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.

Table 5
Lehmann weightings.

Universe	Total 60	No Japan60	Total36	No Japan36
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

Note: 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.

Table 6
Results using equally weighted cash-neutral portfolios.

Universe wing size	Total1	No Japan1	Total2	No Japan2	Total3	No Japan3
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

Note: 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.

ter in filtering out the noise from the return forecast. Overweighting the countries with the highest forecast, as Lehmann weights do, does not generate superior performance as the forecasts contain some noise.

So far, we tested straightforward variations of the US centric version of the Cochrane/Piazzesi model. However, the US financial markets are well-known to dominate other national financial markets (Van Landschoot, 2008). 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:

$$RX^{u}_{t+1,US} = \gamma_o + \sum_{n=1}^{N} \gamma_n F_{t,\mathrm{US}}^{(12n-12)\to 12n} + \varepsilon_{t+1}, \tag{15}$$

while the specification for all other countries follows:

$$RX^{u}_{t+1,j} = \gamma_o + \sum_{n=1}^{N} \gamma_n F_{t,j}^{(12n-12)\to 12n} + \kappa F_{t,\mathrm{US}}^{48\to 60} + \varepsilon_{t+1}, \tag{16}$$

incorporating the forward rate $F_{t,\mathrm{US}}^{48\to 60}$ of the US fixed income market. Trading strategies exploiting this specification are very profitable. This result illustrates the notion that the US fixed income market tends to lead other fixed income markets. Using Lehmann weights the IR of the standard case achieves 1.41 (compare Table 7). 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).

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 a country is admitted to the investment universe.[14]

However, imposing filters does not improve the performance of the strategy significantly.

Ilmanen (1997) and Cochrane and Piazzesi (2005) state that the forecasting power of their models for bond returns increases once the forecasting period increases. In a variation of our trading strategy we forecast total bond returns in the next x months. These forecasts are updated every month. We invest each month $1/x$th of the total capital in the optimal weights of the month and hold the respective portfolio for x months. Such a rolling updating mechanism for portfolio weights is widely used, for example in Jegadeesh and Titman (1993). This way we can use the information obtained by forecasting the total bond excess returns for the next x months, but we can also benefit from a rolling update of the information. We analyze the impact of longer bond return forecasting and holding periods on the returns of the strategy by increasing the forecasting horizon from one to 18 months for the standard Cochrane/Piazzesi specification. The results for Lehmann weighting can be found in Table 8.

Interestingly, we do not find a higher IR when we use a longer forecasting horizon. The performance of the strategy decays relatively rapidly. While a 1-month forecasting horizon returns a considerable information ratio of 0.74, a 3-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. Just like the information ratio, the turnover decreases with longer forecasting horizons monotonously (from 0.50 to 0.10). A lower turnover might reduce the ability of our trading strategy to react to more precise return forecasts through new information in the forward curve. The strong decay in performance for longer forecasting horizons could, therefore, be linked to a higher persistence of portfolio weights. Thus, although there is evidence that longer forecasting periods raise the R^2 of the respective forecasting regressions, this does not translate into higher IRs of the respective strategies.[15]

Facing these results, it appears advisable to use a 1-month forecasting horizon.

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 9. 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

[14] The filters work by restricting the investment universe to the countries which pass the threshold filter in a given period. Lehmann weighting is applied to the countries which pass the threshold test. We try threshold filters with different minimum levels of absolute values of return forecasts (i.e., absolute value of return forecast must be larger than 0.1%, 1%, and 2%). We also apply filters with a threshold equal to the absolute value of return forecasts divided by the standard deviation of the forecast error (absolute value of forecast divided by error standard deviation must be larger than 0.1, 0.3, 0.5, and 1).

[15] Stability tests of these results are performed by using forecasting specifications (5) and (15) on yearly return forecasts. Specification (15) returns the best results, delivering a maximum information ratio of 0.69. The results for forecasts of 1-month indicate a turnover of around 0.50 per month. For the forecasts of 12 months, turnover figures are between 0.13 and 0.14, which is comparably low. Thus, the results stay robust.

Table 7
Results using the Modified Cochrane/Piazzesi specification for the return forecasting.

Weighting Universe	Lehmann		Equal weighting wing size of 3	
	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

Note: This strategy uses the specification detailed in Eqs. (15) and (16) for the forecasting of bond returns. The strategy applies Lehmann weights and equally weighted portfolios with a wing size of three. 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.

Table 8
Results using Lehmann weights to forecast returns for different horizons.

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-Value	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

Note: 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. The strategy is implemented using all countries in our universe.

Table 9
Results using the Modified Cochrane/Piazzesi approach for the return forecasting on different bond tenors.

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

Note: This strategy uses the specification detailed in Eqs. (15) and (16) 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.

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 1-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–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 10. The *IR*s 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 for the restricted factor Γ 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.

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 60 month 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 10. 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. The forward rates appear to contain information which cannot be completely captured in the linear factor combination that is used to determine the restricted factor Γ. Therefore, the restricted 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.

Cochrane and Piazzesi (2005) claim that the restricted factor is unrelated to the *level*, *slope*, and *curvature* of the yield curve. We

Table 10
Performance of strategies using the restricted Cochrane/Piazzesi specification in Eq. (7).

Universe	Static factor generation		Rolling factor generation	
	Total	No Japan	Total	No Japan
μ	0.14%	0.13%	0.06%	0.06%
σ	0.26%	0.28%	0.26%	0.27%
t-Value	4.31	3.77	1.85	1.89
IR	1.87	1.63	0.80	0.82
TO	0.56	0.6	0.51	0.55
T	64	64	64	64

Note: 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 using zero coupon bonds with a tenor of 60 months. The estimation period is 60 months. The restricted Cochrane/Piazzesi specification is determined in two ways (rolling and static approach to determine the weights of the forward rates) and results for both approaches are reported. The weights for the forward rates in the static approach for the determination of the restricted Cochrane/Piazzesi factor are estimated by using all available data and applying these weights at all points in time. The weights for the forward rates in the rolling approach are estimated using a rolling 60 month data window.

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. These factors are defined as

$$level_{t,j} = y^{12}_{t,j}, \quad slope_{t,j} = y^{120}_{t,j} - y^{12}_{t,j},$$
$$curvature_{t,j} = y^{\frac{120-12}{2}}_{t,j} - \frac{1}{2}\left(y^{120}_{t,j} + y^{12}_{t,j}\right), \tag{17}$$

where $y^{u}_{t,j}$ is the zero coupon bond yield with a maturity of u-months for country j at time t. We use these curve factors in the linear regression equation

$$RX^{n}_{t+1,j} = \beta_o + \beta_1 level_{t,j} + \beta_2 slope_{t,j} + \beta_3 curvature_{t,j} + \varepsilon_{t+1,j}. \tag{18}$$

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 11 summarizes the results.

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 19 in the Appendix). 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. Further evidence for the link between the restricted factor Γ and the yield curve factors is found by regressing the rolling restricted factor on the *level, slope*, and *curvature* of the yield curve (compare Table 12). The R^2s 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 and Piazzesi (2005) is not independent from the shape of the term structure of yields.

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 restricted factor is estimated with a rolling window and without the in-sample estimation bias) as forecasting variables:

$$RX^{n}_{t+1,j} = \beta_o + \beta_1 level_{t,j} + \beta_2 slope_{t,j} + \beta_3 curvature_{t,j} + \eta_j \Gamma_{t,j} + \varepsilon_{t+1,j}. \tag{19}$$

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.

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 when estimated in a rolling fashion. Furthermore, the rolling restricted factor is significantly 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 be used to derive profitable trading strategies, 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 13.

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. The rolling restricted model performs 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

Table 11
Performance of trading strategies using level, slope, curvature, and the Restricted Cochrane/Piazzesi factor.

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

Note: 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. The investment universe is unrestricted.

Table 12
Regression of the restricted Cochrane/Piazzesi factor (Γ) on level, slope, and curvature of the yield curve.

Parameter	AUS	CAN	GER	JAP	CH	UK	USA
β_0	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

Note: This table contains the results of regressing the rolling Restricted Cochrane/Piazzesi factor on the level, slope, and curvature of the yield curve. Parameters significant at the 95% confidence level are printed in bold.

Table 13
Performance of different strategies implemented in each country separately.

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
(16)	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

Note: 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 (16) 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.

Canada, Germany, Japan, and the UK). Therefore, on a single country basis there is no clear preference whether to use the restricted or the unrestricted model.

The Modified Cochrane and Piazzesi approach in Eq. (16) delivers in general the best 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 (16) in each country separately and forming an equally weighted portfolio results in a high *IR* of 1.24.

8. Bond return forecasts with Bayesian model averaging

The previous sections analyze the economic link between the forward curve and future bond returns using an ordinary least square regression setup. The specifications of the regressions are motivated by economic reasoning. This section complements these economic analyses by running our strategy with Bayesian model averaging (BMA) which is a rather statistics-driven methodology.

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. Bayesian model averaging is one of the methods which is suggested in the literature to deal with this model uncertainty and can be outlined as follows. Suppose there is a set of $i = 1,\ldots,k,\ldots,q$ models M_i. For every moment in time we calculate the posterior probability, $p(M_k|data)$, that model k is the correct model. We have

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

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 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 $B_{ik} = \frac{p(data|M_i)}{p(data|M_k)}$ can be approximated by the so-called Bayesian Information criterion (BIC) approximation

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

The derivation of this approximation is detailed in Hastie et al. (2001). As the BIC value is a 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 a $q \times 1$ vector assigning probabilities to each of the q regression models, $\mathbf{P}_{t,j} = [p(M_1|data),\ldots,p(M_q|data)]$. We also have a $q \times (m+1)$ matrix of OLS regression coefficients (m regressors plus one constant), $\boldsymbol{\Theta}_{j,t}$. Combined with our knowledge of the m forward rates at time t, represented by $\mathbf{F}_{j,t}$, we can now generate a return forecast for country j

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

This methodology is run for each country separately to come up with a return forecast.

In our implementation of Bayesian model averaging we use the forward rates of *all* countries as explaining variables for the future bond returns of *one specific* country. Then we generate all permutations of the explaining variables (i.e., of the forward rates of the different countries) and regress future zero bond returns of a country on these permutations. We designate each permutation as its own model M_i. Using the Bayesian model averaging methodology, we assign a probability to each forecasting model of a country and calculate a weighted average of the models' bond return forecasts for a specific country. The average forecasts we obtain for the countries in our universe are taken as input into our portfolio construction rules. We can now compare our previous approach with Bayesian model averaging.

Bayesian model averaging improves the performance of our trading strategy greatly (see Table 14 for details). Compared to the standard specification summarized in Table 5 the information ratio increases significantly from 0.74 to 1.67 when Lehmann weights are applied. If Japan is eliminated out of the investment universe, the increase is even more pronounced (from 0.90 in the standard specification to 2.24 for Bayesian model averaging). Even

Table 14
Results using Bayesian model averaging in the return forecasting.

Weighting Universe	Lehmann		Equal weighting wing size of 3	
	Total	No Japan	Total	No Japan
μ	0.10%	0.15%	2.54%	3.05%
σ	0.21%	0.23%	7.57%	8.11%
t-Statistic	3.86	5.18	2.69	3.01
IR	1.67	2.24	1.16	1.31
TO	0.18	0.19	0.18	0.16
T	64	64	64	64

Note: This strategy uses the Modified Cochrane/Piazzesi specification and Bayesian model averaging 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.

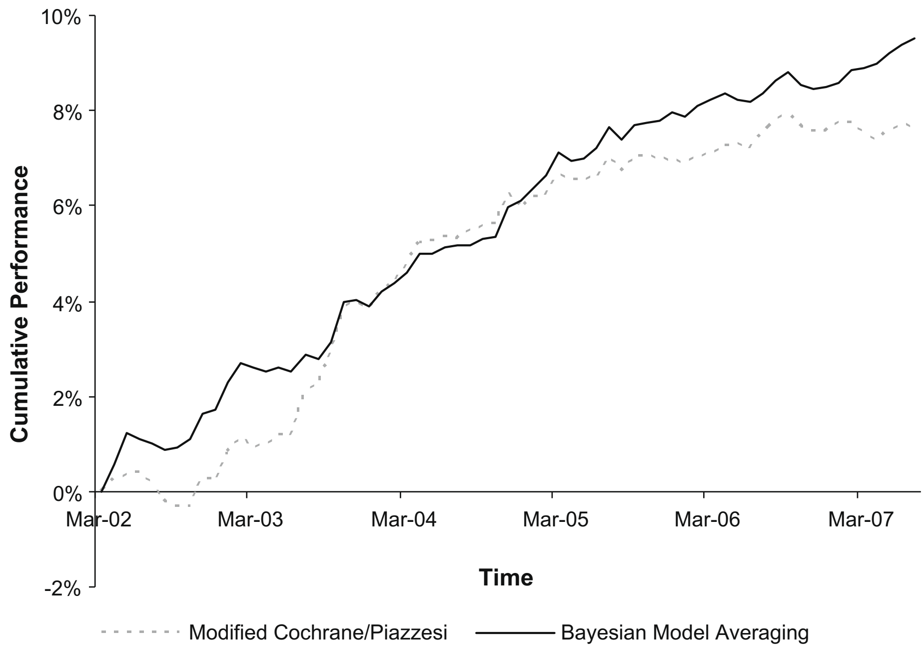

Fig. 2. Classical forecasts (Modified Cochrane/Piazzesi) versus Bayesian model averaging. *Note:* Bayesian model averaging provides superior strategy returns by delivering a higher information ratio and less variable performance across different time periods.

for the Modified Cochrane/Piazzesi specification, which delivered the best results in the previous analyses, the improvement is noticeable: Using Lehmann weights, the Bayesian model averaging delivers an IR which is 18% higher (*IR*s of 1.41 and 1.67 for the Modified Cochrane/Piazzesi and Bayesian model averaging approach, respectively). We repeat our analysis using a wing size of 3. The performance of the BMA strategy decreases when using equally weighted wing portfolios instead of Lehmann weights (*IR* decreases from 1.67 to 1.16 for the whole universe). However, the model averaging still improves the performance compared to previous specifications. For the total universe, the *IR* increases to 1.16 compared to 0.66 in the base case and 0.65 for the Modified Cochrane/Piazzesi approach.

Fig. 2 plots the cumulative performance of the Bayesian model averaging specification and the Modified Cochrane/Piazzesi specification. The two strategies apply Lehmann weights and exclude Japan from the investment universe. The Bayesian model averaging outperforms the Modified Cochrane/Piazzesi specification. Particularly interesting is that the Bayesian model averaging results in a stable and positive performance even in recent years. The Modified Cochrane/Piazzesi strategy, in contrast, leveled out since late 2006.

In summary, we find that Bayesian model averaging helps to improve the reliability of bond return forecasts. This enhanced methodology leads to a significant improvement of the performance of our investment strategies. The return forecasts with a weighted average of different forecasting specifications appears to diversify noise, leading to a more stable forecast.

9. Panel regression of strategy performance in each country on the national yield curve components

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.[16]

With the US economy and capital market being dominant in the world markets, the US yield curve is a good choice to link strategy returns and curve components. Fig. 3 depicts the *slope* of the US yield curve and the performance of the base case using Eq. (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.

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. 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). The analysis estimates the parameters of the following specifications:

$$RS_{t,j} = \beta_0^{RS} + \beta_l^{RS} level_{t,j} + \beta_s^{RS} slope_{t,j} + \beta_c^{RS} curvature_{t,j} + \varepsilon_{t,j}, \tag{23}$$

$$RS_{t,j} = \beta_0^{RS} + \beta_l^{RS} level_{t,j} + \varepsilon_{t,j}, \tag{24}$$

$$RS_{t,j} = \beta_0^{RS} + \beta_s^{RS} slope_{t,j} + \varepsilon_{t,j}, \tag{25}$$

$$RS_{t,j} = \beta_0^{RS} + \beta_c^{RS} curvature_{t,j} + \varepsilon_{t,j}, \tag{26}$$

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

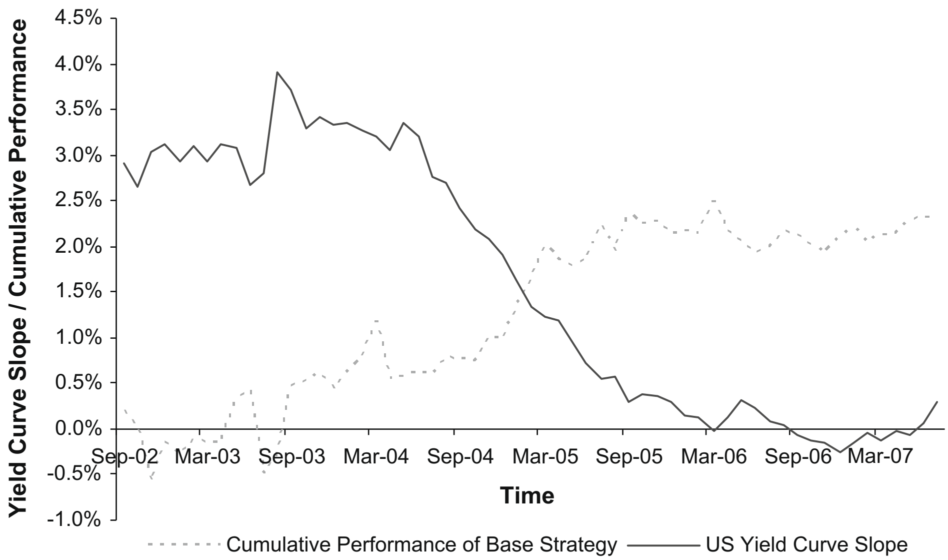

Fig. 3. Performance of the base case strategy and the US yield curve slope. *Note:* This graph depicts the yield curve slope and the performance of the base case strategy. The base case strategy invests in Lehmann weights according to bond price return forecasts from specification (5).

Table 15
Impact of the yield curve on the performance of the modified strategy using forecasting Eq. (16) and a panel regression.

Rolling return period	1	6	1	6	1	6	1	6
β_0^{RS}	**0.00**	**0.01**	−0.00	0.00	−0.00	**0.01**	−**0.00**	−**0.02**
	(**3.00**)	(**7.32**)	(−**1.51**)	(**1.66**)	(−**0.81**)	(**4.67**)	(−**2.62**)	(−**4.57**)
β_l^{RS}	−0.27	−**1.87**					**0.80**	5.78
	(−**1.46**)	(−**3.28**)					(**2.41**)	(**5.40**)
β_s^{RS}			**2.06**	**9.97**			**2.36**	**25.50**
			(**4.43**)	(**6.87**)			(**2.00**)	(**7.30**)
β_c^{RS}					**10.95**	**38.75**	5.80	−**31.50**
					(**4.86**)	(**5.25**)	(**1.39**)	(−**2.55**)
R^2	0.00	0.03	0.06	0.14	0.08	0.09	0.09	0.19

Note: 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 (16). 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^2s of the regressions. Parameters significant at the 95% confidence level are printed in bold.

where $RS_{t,j}$ is the return of the analyzed trading strategy at time t for country j.

Using standard specification (5) to generate strategy returns, a very low explanatory power is obtained for most specifications.[17]

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 13 the strategy works well in the US, but not so well in Germany). Using the Modified Cochrane/Piazzesi approach from specification (16) delivers more consistent profits across countries (compare Table 13). Therefore, we invest according to the forecasts of specification (16) in each country and panel-regress the resulting national strategy returns on the characteristics of the respective national yield curve. Table 15 shows that 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 strategy performance 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. In the multivariate panel regression the *level* and *slope* are the only significant factors with parameters of 0.80 and 2.36, respectively (t-statistic of 2.41 and 2.00).

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. For the 6-month returns as dependent variables, 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). For the multivariate case 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). Thus, we find a clear link between the performance trend of a strategy and the shape of the yield curve.

The results in this section show that the positive link of the *slope* of the yield curve and the strategy performance is significant and robust. While we find some sign changes for the level and the curvature when moving from a univariate to a multivariate specification, results are still fairly robust. 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^2s are moderate and there appear to be other important factors with

[17] Results not reported here for brevity.

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 10 years and, therefore, the power of this analysis has limitations.

10. Comparison of our strategy with alternative forecasting approaches

Having established the stability of our strategy across different specifications, we concentrate on the comparison of our strategy with the performance of other known fixed income trading strategies. We use two alternative methodologies as benchmarks for our approach.

The first methodology forecasts future bond returns directly by using fixed income indicators in a regression approach. In particular, we use the short rate momentum, the slope of the yield curve, and the real yield to forecast future returns of bonds with 5 years to maturity. Ilmanen (1997) uses similar variables in his analysis of fixed income trading strategies. We continue to use the yield curve slope definition from Eq. (17). The rational for the use of this variable is the notion that a steeper yield curve slope may reflect the market expectation of higher interest rates (compare Ilmanen, 1996). This would lead to falling bond prices. The real yield includes the inflation into the consideration of capital market yields. Thus, it gives a cleaner picture of the income earned on a fixed income investment. The short rate momentum reflects the 3 month change in the 1-month zero coupon yield. The rational behind this forecasting measure is the notion that interest rates tend to exhibit momentum. This momentum leads to shifts of the yield curve and subsequently to price movements in the underlying bonds. By using momentum in central bank rates Conover et al. (1999) apply a similar rational to the equity market. We use short rate momentum, yield curve slope, and real yield in a regression approach to forecast the excess bond returns of 5 year bonds 1-month ahead. The regressions use a rolling window to prevent in-sample forecasting. A cash-neutral portfolio is then formed by using the return forecasts of these regressions and one of our two portfolio construction methodologies (Lehmann weights and equally weighted wing portfolios). The resulting performance is compared with our previous results.[18]

Using this approach with an equally weighted portfolio, we arrive at a reasonably good performance (compare Table 16). Using the short rate momentum to forecast 5 year bond returns in the next month results in the worst performance with an information ratio of −0.28. The turnover is with 0.40 higher than for the slope and the real yield. Using the slope and the real yield in univariate forecasting regressions results in information ratios of 0.22 and 0.90, respectively. The real yield as forecasting instrument can even generate a positive performance which is statistically significant (*t*-statistic of 2.05). However, when reducing the estimation period in the regressions from 60 months to 36 months, the information ratios decrease strongly.[19]

The best performance (*IR* of 0.37) is found using the slope to forecast future bond returns. We conclude from this exercise that there is value in using the short rate momentum, real yield, and yield curve slope to forecast future bond returns. However, the results are rather volatile and depend strongly on the parametrization. Compared to our base case in Table 5 and the Bayesian model averaging approach in Table 14 (information ratios in excess

Table 16
Results using well-known forecasting variables for bond returns.

Forecast variables	Short rate momentum	Slope	Real yield	Short rate momentum/ slope/real yield
μ	−0.02%	0.02%	0.08%	0.05%
σ	0.26%	0.28%	0.29%	0.29%
t-Statistic	−0.63	0.50	2.05	1.33
IR	−0.28	0.22	0.90	0.59
TO	0.40	0.28	0.24	0.53
T	62	62	62	62

Note: This table contains the results of forecasting future bond returns with regressions and investing accordingly. Forecasting variables are the short rate momentum, slope of the yield curve, and the real yield. The strategies are implemented with equally weighted portfolios with a wing size of three. 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 for the forecasting regressions is a rolling window of 60 months. The investment universe covers all countries in our sample.

of 0.65 and 1.15, respectively), the results in this section are in general less stable and the performance weaker.

Another methodology to forecast future bond returns applies the Nelson and Siegel (1987) yield curve model. Our approach follows Diebold and Li (2006) in fitting the following specification to the yield curve of country j at time t[20]:

$$y_{t,j}^{NS,u} = \beta_{1,t,j} + \beta_{2,t,j} \cdot \left(\frac{1 - e^{-\lambda u}}{\lambda u}\right) + \beta_{3,t,j} \cdot \left(\frac{1 - e^{-\lambda u}}{\lambda u} - e^{-\lambda u}\right), \tag{27}$$

for the u-month zero coupon yield and country j at time t. The parameter vector $\theta_{t,j} = \{\beta_{1,t,j}, \beta_{2,t,j}, \beta_{3,t,j}\}$ is estimated by minimizing the sum of the squared errors:

$$\hat{\theta}_{t,j} = \arg\min_{\theta_{t,j}} \sum_{n=1}^{N} \varepsilon_{12n,t,j}^2, \tag{28}$$

with N being the number of yields which are fitted and

$$\varepsilon_{u,t,j} = y_{t,j}^{NS,u} - y_{t,j}^{u}. \tag{29}$$

Diebold and Li (2006) show that a simultaneous estimation of the parameter λ provides only limited benefit. Thus, we follow Diebold and Li (2006) by setting $\lambda = 0.0609$. As we focus only on the yields at the 12, 24, 36, 48, and 60 month points, we restrict ourselves to fitting the model to these yield curve points. Having fitted the model to our five curve points for all months in our sample, the time-series of $\hat{\theta}_j$ up to time t is used to forecast $\theta_{t+1,j}$. We continue to follow Diebold and Li (2006) by applying an AR (1) process to forecast the elements of $\theta_{t+1,j}$ (i.e., $\beta_{1,t+1,j}$, $\beta_{2,t+1,j}$, and $\beta_{3,t+1,j}$). The forecasted parameter vector $\hat{\theta}_{t+1,j}$ is used to determine $\hat{y}_{t+1,j}^{NS,59}$, the yield of a zero bond with 4 years and 11 months to maturity 1-month in the future (i.e., the remaining time to maturity at $t + 1$ of a 5 year bond bought at t). Given that we know the zero coupon yield of a 5 year bond today, we can calculate the expected returns on such a bond as

$$\widehat{R}_{t+1,j} = \ln(\widehat{P}_{t+1,j}^{59}) - \ln(P_{t,j}^{60}) = 60 \cdot y_{t,j}^{60} - 59 \cdot \hat{y}_{t+1,j}^{NS,59}. \tag{30}$$

We apply this approach to all countries in our sample to determine forecasts for excess returns. These excess return forecasts are used to construct equally weighted wing portfolios or Lehmann portfolios.

Using the approach suggested in Diebold and Li (2006) and an estimation period of 60 months to fit the AR (1) process leads to information ratios in excess of 0.5 (compare Table 17). Although

[18] As we use a short rate momentum of 3-months in our regressions, our backtest covers 2-months less than for our standard case.

[19] Results not reported for brevity.

[20] A possible extension to this approach is Almeida and Vicente (2008) who successfully use arbitrage-free parametric polynomial models to forecast the term structure.

Table 17
Results using the bond return forecasting approach by Diebold and Li (2006).

Estimation period	Lehmann		Equal weighting	
	60	36	60	36
μ	0.05%	0.00%	0.05%	0.00%
σ	0.29%	0.29%	0.29%	0.29%
t-Statistic	1.47	0.45	1.28	0.27
IR	0.64	0.00	0.56	0.10
TO	0.30	0.37	0.38	0.44
T	64	88	64	88

Note: This table contains the results of forecasting future bond returns with a methodology suggested by Diebold and Li (2006) and investing accordingly. In this methodology bond price changes are derived by predicting the parameters of the yield curve model in Nelson and Siegel (1987). The forecasts are implemented in equally weighted portfolios with a wing size of three. 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 for the forecasting regressions is a rolling window of 60 months. The investment universe covers all countries in our sample.

Lehmann weights perform slightly better than an equally weighted portfolio with a wing size of 3 (*IR*s of 0.64 and 0.56, respectively), the portfolio construction methodology appears to have little impact on performance. However, when the estimation period for the AR (1) process is reduced to 36 months, the performance drops significantly for both portfolio construction methods (information ratios below 0.1). Compared to information ratios clearly in excess of 0.7 for most of our Cochrane/Piazzesi variations (compare, e.g., the base case in Table 5 or the Bayesian model averaging in Table 14), the Diebold and Li (2006) approach is outperformed in terms of stability as well as performance. Since the fit of the Diebold and Li (2006) approach to contemporaneous yield curves is reasonably good[21], it appears that the forecasts for the parameters $\beta_{1,t+1,j}$, $\beta_{2,t+1,j}$, and $\beta_{3,t+1,j}$ are the more difficult step, leading to suboptimal return forecasts. Thus, the forward looking information stored in the forward curve appears to be the superior predictor in trading strategies.[22]

In the previous paragraphs it is established that the usage of a trading strategy inspired by Cochrane and Piazzesi (2005) delivers a strong performance compared with other forecasting approaches. Between the performance of the strategies we find low correlations. Running portfolios with the BMA approach (wing size of 3, full universe) and comparing the performance with the Diebold and Li (2006) as well as the real yield/slope/short rate momentum forecast, we obtain correlations of 0.14 and −0.25, respectively. Comparing the two benchmark strategies with the standard forecast from Eq. (5) under equal weighting and wing size of 3 results in similarly low correlations of 0.31 and −0.39, respectively. Thus, a portfolio running all three different approaches would profit from a considerable diversification effect.

In summary, we compare the performance of our forecasting methodology to a range of alternative forecasting approaches. Although traditional forecasting variables – such as short rate momentum, yield curve slope, and real yield – achieve a reasonable performance in a regression based forecasting approach, they are dominated by our methodology. The same applies to a more complex forecasting model which uses the procedure described in Diebold and Li (2006) to forecast the yield curve and bond returns.

[21] The fit of the model is analyzed by determining the mean squared error across the 5 yield curve points we analyze. Then we average the mean squared error for each country over time. We arrive at values which range between 0.0000011 for the UK and 0.0000418 for Japan.

[22] These results hold true for a range of different specifications. For example, we also use AR(2), AR(3), and vector autoregressive processes to forecast $\theta_{t+1,j}$, but obtained similar results.

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 found to be stable in a range of different market environments across the globe. When applying the model by Cochrane and Piazzesi (2005) in our investment strategies, they deliver the best results when implemented with a relatively short forecasting horizon of 1-month. An alternative forecasting specification developed in this article improves the forecasting power for international fixed income returns and arrives at strategies with an information ratio in excess of 1.5. The usage of Bayesian model averaging further improves the performance of the trading strategy. Another finding is that the performance of the trading strategies is influenced by the shape of the yield curve. Therefore, the extent of the information stored in the forward curve appears to depend on the yield curve shape. Compared to other well-known fixed income trading strategies our approach arrives at a higher and more stable performance.

Table 18
Correlations of explaining variables.

	$F^{0\to12}$	$F^{12\to24}$	$F^{24\to36}$	$F^{36\to48}$	$F^{48\to60}$
AUS					
$F^{0\to12}$	1.00	0.77	0.66	0.57	0.45
$F^{12\to24}$	0.77	1.00	0.97	0.94	0.88
$F^{24\to36}$	0.66	0.97	1.00	0.99	0.95
$F^{36\to48}$	0.57	0.94	0.99	1.00	0.98
$F^{48\to60}$	0.45	0.88	0.95	0.98	1.00
CAN					
$F^{0\to12}$	1.00	0.94	0.78	0.68	0.56
$F^{12\to24}$	0.94	1.00	0.88	0.81	0.71
$F^{24\to36}$	0.78	0.88	1.00	0.97	0.91
$F^{36\to48}$	0.68	0.81	0.97	1.00	0.98
$F^{48\to60}$	0.56	0.71	0.91	0.98	1.00
GER					
$F^{0\to12}$	1.00	0.93	0.85	0.78	0.72
$F^{12\to24}$	0.93	1.00	0.97	0.89	0.84
$F^{24\to36}$	0.85	0.97	1.00	0.95	0.94
$F^{36\to48}$	0.78	0.89	0.95	1.00	0.97
$F^{48\to60}$	0.72	0.84	0.94	0.97	1.00
JAP					
$F^{0\to12}$	1.00	0.83	0.73	0.50	0.64
$F^{12\to24}$	0.83	1.00	0.89	0.72	0.83
$F^{24\to36}$	0.73	0.89	1.00	0.90	0.93
$F^{36\to48}$	0.50	0.72	0.90	1.00	0.90
$F^{48\to60}$	0.64	0.83	0.93	0.90	1.00
CH					
$F^{0\to12}$	1.00	0.94	0.87	0.79	0.70
$F^{12\to24}$	0.94	1.00	0.95	0.89	0.81
$F^{24\to36}$	0.87	0.95	1.00	0.92	0.85
$F^{36\to48}$	0.79	0.89	0.92	1.00	0.96
$F^{48\to60}$	0.70	0.81	0.85	0.96	1.00
UK					
$F^{0\to12}$	1.00	0.91	0.83	0.82	0.81
$F^{12\to24}$	0.91	1.00	0.98	0.96	0.93
$F^{24\to36}$	0.83	0.98	1.00	0.99	0.96
$F^{36\to48}$	0.82	0.96	0.99	1.00	0.98
$F^{48\to60}$	0.81	0.93	0.96	0.98	1.00
USA					
$F^{0\to12}$	1.00	0.95	0.86	0.76	0.69
$F^{12\to24}$	0.95	1.00	0.96	0.87	0.83
$F^{24\to36}$	0.86	0.96	1.00	0.94	0.94
$F^{36\to48}$	0.76	0.87	0.94	1.00	0.95
$F^{48\to60}$	0.69	0.83	0.94	0.95	1.00

Note: This table contains the correlations between the forward rates used in the Cochrane/Piazzesi Model for all countries in the chosen universe.

Table 19
Correlation of the Restricted Cochrane and Piazzesi (2005) factor and the level, slope, and curvature of the yield curve.

	Γ	Level	Slope	Curve
AUS				
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
Curvature	0.06	−0.50	0.90	1.00
CAN				
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
Curvature	0.51	−0.51	0.88	1.00
GER				
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
Curvature	0.30	−0.26	0.79	1.00
JAP				
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
Curvature	0.27	0.34	0.60	1.00
CH				
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
Curvature	0.39	−0.66	0.78	1.00
UK				
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
Curvature	0.00	−0.47	0.75	1.00
USA				
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
Curvature	0.56	−0.79	0.95	1.00

Note: This table contains the correlations between *level*, *slope*, *curvature*, and the Restricted Cochrane/Piazzesi factor for all the countries in the sample.

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Appendix

Tables 18 and 19.

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