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The Role of an Aligned Investor Sentiment Index in Predicting Bond Risk Premia of the United States

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In this paper, we develop a new investor sentiment index that is aligned with the purpose of predicting the excess returns on government bonds of the United States (US) of maturities of 2-, 3-, 4-, 5-year. By eliminating a common noise component in underlying sentiment proxies using the partial least squares (PLS) approach, the new index is shown to have much greater predictive power than the original principal component analysis (PCA)-based sentiment index both in- and out-of-sample, with the predictability being statistically significant, especially for bond premia with shorter maturities, even after controlling for a large number of financial and macro factors, as well as investor attention and manager sentiment indexes. Given the role of Treasury securities in forecasting of output and inflation, and portfolio allocation decisions, our findings have significant implications for investors, policymakers and researchers interested in accurately forecasting return dynamics for these assets.

JEL classification: C22; C53; G12; G17

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1. Introduction

The expectations hypothesis of the term structure of interest rates suggests that yield of a given maturity should equal the average of expected short-term rates over the period until maturity, which in turn implies that the expected risk premia on bonds cannot be forecasted. However, an already large and growing literature has consistently highlighted the forecastability of United States (US) government bonds (see for example, Cochrane and Piazzesi (2005), Cooper and Priestly (2009), Ludvigson and Ng (2009, 2011), Duffie (2011), Joslin et al., (2014), Greenwood and Vayanos (2014), Cieslak and Povala (2015), Zhu (2015), Ghysels et al., (2018), Gargano et al., (2019), Çepni et al., (2019a, b), Balcilar et al., (forthcoming)).[1] In general, the empirical evidence highlights the role of macro and financial factors, often extracted from large data sets, in predicting bond premia, over and above the so-called CP factor of Cochrane and Piazzesi (2005), constructed as a linear combination of forward rates.

Different from the above studies, Laborda and Olmo (2014) highlighted the importance of behavioral predictors, measuring investor sentiment regarding the state of the economy, in capturing future movements of the US excess bond returns, beyond the factors discussed above.[2] In this regard, Baker and Wurgler (2012), while analyzing comovement between government bonds and bond-like stocks, argue that an explanation for the predictability of the bond market is jointly based on shocks to real cash flows, shocks to discount rates and time-varying investor sentiment that is linked to market risk aversion. Note that, Laborda and Olmo (2014) used the investor sentiment index of Baker and Wurgler (2006, 2007), which was shown to explain movements of the US equity market, and was based on the first principal component of the correlation matrix of six proxies for sentiment. These proxies, orthogonalized to several macroeconomic variables, were: the closed-end fund discount; New York Stock Exchange (NYSE) share turnover; the number of initial public offerings (IPOs); the average first-day returns; the share of equity issues in total equity and debt issues, and; the dividend premium.

Econometrically speaking, the first principal component, as used by Baker and Wurgler (2006, 2007), is indeed the best combination of the six proxies that represents the highest percentage of the total variations

[1] Notable earlier studies include Keim and Stambaugh (1986), Fama and Bliss (1987), Fama and French (1989), and Campbell and Shiller (1991).

[2] Nayak (2010) explored the impact of investor sentiment on corporate bond yield spreads, and found that corporate bonds appear underpriced (with high yields and spreads) when beginning-of-period sentiment is low, and overpriced (with low yields and spreads) when beginning-of-period sentiment is high.

of the proxies. Since all the proxies may have approximation errors to the true but unobservable investor sentiment, and these errors are parts of their variations, the first principal component can potentially contain a substantial amount of common approximation errors that are not relevant for forecasting asset returns (Bai and Ng, 2008; Boivin and Ng, 2006). Given this, we align the investor sentiment measure with the purpose of explaining the excess bond returns by extracting the most relevant common component from the proxies. In other words, we separate out information in the proxies that is relevant to the expected bond returns from the error or noise, by using the partial least squares (PLS) method originally developed by Wold (1966, 1975), and applied to financial data by Kelly and Pruitt (2013, 2015). Note that, in this regard, we follow Huang et al., (2015), who used this approach to show that this new (aligned investor sentiment) index has much greater predictive power than the original metric developed by Baker and Wurgler (2006, 2007) in forecasting aggregate US stock returns, given that this new index does incorporate efficiently all the relevant forecasting information from the six proxies.

Once we develop the new aligned investor sentiment index, we compare its predictive performance for the excess bond returns of the US with that of the principal component analysis (PCA)-based index of Baker and Wurgler (2006, 2007), after controlling for the CP factor, a large number of macro and financial factors (as outlined by Ludvigson and Ng (2009, 2011)), and a newly-developed investor attention index of Chen et al., 2019 in a linear predictive regression framework. Note that, the decision to also consider the investor attention index in our analysis, derived from a common component derived of twelve major investor attention proxies (abnormal trading volume, extreme returns, past returns, nearness to 52-week high and nearness to historical high, analyst coverage, changes in advertising expenses, mutual fund inflow, mutual fund outflow, and media coverage, search-traffic on the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system, and Google search volume), was due to the fact that Chen et al., (2019) showed that the investor attention index outperformed investor sentiment indexes in forecasting US stock returns. In the process, our paper aims to add to the work of Laborda and Olmo (2014) based on the PCA generated investor sentiment index, by first developing a new investor sentiment index using PLS, and then comparing the forecasting performances of these two investor sentiment indexes developed using two alternative econometric approaches of combining information from six alternative sentiment-related proxies, given the role of other important predictors used in the literature. Specifically, we conduct in-sample predictability analysis, as well as out-of-sample forecasting of US bond premia of maturities of two- to five-year (relative to one-year bonds) covering the monthly period of 1980:01-2016:12, with an out-of-sample period of

1995:01 to 2016:12, over which we forecast the two- to five-year bond premia at horizons of one-, two-three-, six-, nine-, and twelve-month-ahead. The remainder of the paper is organized as follows: Section 2 provides the description of the data and methodology, while Section 3 presents the empirical results, with Section 4 concluding the paper.

2. Data and Methodology

Price data for one through five-year zero coupon bonds at monthly frequency are obtained from the Fama and Bliss (1987) dataset, which is available at the Center for Research in Security Prices (CRSP).[3] In order to analyze the predictability of excess bond returns, we run predictive regressions of the type commonly used in the empirical finance literature, formulated as

$$rx_{t+1}^{(n)} = \alpha_0 + \beta' Z_t + \varepsilon_{t+1}, \tag{1}$$

where $rx_{t+1}^{(n)}$ is the continuously compounded excess return on an n-year zero coupon bond in period $t+1$. Besides the benchmark random-walk (RW) model, we estimate primarily four additional models as part of our main analysis, with Z_t including the single forward factor (CP) of Cochrane and Piazzesi (2005)[4]; the CP, and macro and financial factors (LN) constructed by Ludvigson and Ng (2009, 2011) using dynamic factor analysis,[5]; the PCA-based investor sentiment index besides the CP and LN factors, and; the PLS-based investor sentiment index besides the CP and LN factors. Clearly, comparing the fourth and fifth models with the first three will tell us whether investor sentiment indexes (construction of which we discuss in detail below) add value to forecasting of bond premia, while comparing between the fourth and fifth model will inform us whether our PLS-based investor sentiment index can outperform the traditional PCA-based index.

[3]In line with Cochrane and Piazzesi (2005), we use the following notation for the (log) yield of an n-year bond $y_t^{(n)} \equiv -\frac{1}{n} p_t^{(n)}$, where $p_t^{(n)} = lnP_t^{(n)}$ is the log bond price of the n-year zero coupon bond at time t. A forward rate at time t for period ($t+n-1$, $t+n$) is defined as: $f_t^{(n)} \equiv p_t^{(n-1)} - p_t^{(n)}$. The log holding period return from buying an n-year bond at time t and selling it as an $n-1$ year bond at time $t+1$ is: $r_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)}$. The excess return on an n-year discount bond over a short-term bond is then the difference between the holding period returns of the n-year bond and the 1-period interest rate, $rx_{t+1}^{(n)} \equiv r_{t+1}^{(n)} - y_t^{(1)}$.

[4]To compute the CP predictor, we first regress average excess returns across maturities at each time t on the one-year yield and the forward rates $f_t \equiv [y_t^{(1)} f_t^{(2)} f_t^{(3)} f_t^{(4)} f_t^{(t)}]^T$: $\overline{rx}_{t+1} = \gamma_0 + \gamma^T f_t + \overline{\varepsilon}_{t+1}$, where the average excess log returns across the maturity spectrum is defined as: $\overline{rx}_{t+1} \equiv \frac{1}{4} \sum_{n=2}^{5} rx_{t+1}^{(n)}$. The CP predictor is then obtained from: $CP_{t+1} = \gamma_0 + \gamma^T f_t$.

[5]Data obtained from Sydney C. Ludvigson's website at: https://www.sydneyludvigson.com/data-and-appendixes/.

Although Ludvigson and Ng (2009, 2011) find that nine common factors explain more than 50% of the variation in macro series, we follow Cochrane and Piazzesi (2005) and form a single predictor, F_s, by estimating a regression of average excess returns on the set of estimated nine factors. Hence, we construct a linear combination of factors that explains a large fraction of the variation in future excess returns by running the following regression:

$$\frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)} = \gamma_0 + \gamma_1\widehat{F_{1t}} + \gamma_2\widehat{F_{1t}^3} + \gamma_3\widehat{F_{2t}} + \gamma_4\widehat{F_{3t}} + \gamma_5\widehat{F_{4t}} + \gamma_6\widehat{F_{5t}} + \gamma_7\widehat{F_{6t}} + \gamma_8\widehat{F_{7t}} + \gamma_9\widehat{F_{8t}} = F_s \quad (2)$$

In their seminal papers, Baker and Wurgler (2006, 2007) construct a novel investor sentiment index (Inves.Sent.BW) that uses PCA to aggregate the information from six sentiment proxies: the closed-end fund discount, which is the average difference between the net asset value of closed-end stock fund shares and their market prices; New York Stock Exchange (NYSE) share turnover, based on the ratio of reported share volume to average shares listed from the NYSE Fact Book; the number of IPOs; the average first-day returns; the share of equity issues in total equity and debt issues, which is a measure of financing activity, and; the dividend premium.[6] To construct our aligned investor sentiment index (Inves.Sent.PLS), we apply the PLS method to the same six proxies.

The PLS method is applied by following the two-step procedure explained in Friedman et al., (2001). The algorithm starts by standardizing each proxies x_j ($j = 1, \ldots, p$) to have zero mean and unit variance. Then, univariate regression coefficients $\widehat{\gamma_{1j}} = \langle x_j, y \rangle$ are stored for each j. From this, the first PLS direction $z_1 = \sum_j \widehat{\gamma_{1j}} x_j$ is acquired as the weighted sum of the vector of univariate regression coefficients and original set of sentiment proxies. Thus, the construction of the PLS direction includes the degree of association between excess bond returns and common factors. In the following step, the 'target' variable y is regressed on z_1, resulting in a coefficient θ_1, and then all inputs are orthogonalized with respect to z_1. This process is iterated until PLS produces a sequence of $l < p$ orthogonal directions.

Since PLS uses the excess bond returns to construct the directions, its solution path is a non-linear function of excess bond returns. As suggested in Bianchi et al., (2019), it differs from PCA in the sense that, while PCA finds directions that maximize only the variance, PLS aims for the directions that have high variance and high correlation with the target variable simultaneously. More specifically, the mth PLS

[6]The six individual investor sentiment proxies, as well as the overall PCA-based sintement index data are available from Professor Jeffrey Wurgler's website at: http://people.stern.nyu.edu/jwurgler/.

direction $\widehat{\gamma_m}$ solves the following optimization problem:

$$\begin{aligned} \max_{\alpha} \quad & Corr^2(y, X_\alpha)Var(X_\alpha), \\ \text{subject to} \quad & \|\alpha\| = 1, \quad \alpha' S \widehat{\gamma_l} = 0, \quad l = 1, ..., m-1 \end{aligned} \tag{3}$$

where S represents the sample covariance matrix of the x_j.

We select the first common component as new investor sentiment index, which efficiently incorporates all the relevant forecasting information from the sentiment proxies for excess bond returns. We repeat this exercise and obtain different investor sentiment indices for each the four maturities of bond premium.

As an additional analysis, to check if the performance of our PLS-based investor sentiment index can be improved by including information on investor attention, we consider two indices developed by Chen et al., (2019) based on the PLS approach. The first one of these indexes is the attention index (Inves.Att) is estimated from seven attention proxies (abnormal trading volume, extreme returns, past returns, nearness to the NYSE 52-week high, nearness to the NYSE historical high, analyst coverage, and changes in advertising expenses) starting from 1980:01. As far as the second one is concerned, called the augmented attention index (Inves.Att.Aug), is estimated from twelve attention proxies (which includes the seven long-sample proxies mentioned above and five short-sample (starting from 2004:01) proxies: media coverage, mutual fund inflow, mutual fund outflow, search-traffic on EDGAR, and Google search volume).[7]

Based on the availability of data of the bond premia and the various predictors, our sample period runs from 1980:01 to 2016:12. In order to examine how much of the variation in excess bond returns can be explained by different investor sentiment indexes, we first run in-sample regressions as shown in Eq.(1). We then utilize a recursive out-of-sample forecasting exercise from 1995:01 to 2016:12, given an in-sample of 1980:01 to 1994:12, to analyze the predictive accuracy of the various sentiment indexes by adding each explanatory variable (as discussed above) to the RW model one at a time. For each month, we produce a sequence of six h-month-ahead forecasts, i.e., $h = 1, 2, 3, 6, 9, 12$. Note that we choose in- and out-of-sample periods in a way that ensures the latter covers most of the important turmoil periods experienced in financial markets. Finally, we use the predictive accuracy tests of the Harvey et al. (1997) to compare the statistical significance of forecast performances relative to the RW model.

[7]The data on the two overall indexes (but not the underlying proxies) are available for download from the website of Professor Guofu Zhou at: http://apps.olin.wustl.edu/faculty/zhou/.

3. Empirical Results

In this segment of the paper, we conduct in-sample and out-of-sample tests of predictability for the bond premia of four different maturities with our various predictors, but with the primary focus being on the PCA- and PLS-based sentiment indexes. Table 1 presents the estimates of the unrestricted and restricted versions of the model incorporating the different investor sentiment indexes. The results suggest that these regressions express a sizeable percentage of next month's excess bond returns variation across all maturities. Although the predictive content of the model that includes Inves.Sent.PLS index and the model with Inves.Sent.BW are nearly same when we compare the R^2 values, we observe that the Inves.Sent.PLS index is the only measure that has statistically significant predictive power, consistently for the bonds at all maturities. Furthermore, the in-sample regressions show that the R^2 reaches nearly 50% for 2-year and 3-year excess bond returns, and provides strong evidence of an investor sentiment factor in bond risk premia especially relevant for shorter maturities. The point estimate of the coefficient on the Inves.Sent.PLS index is always positive and economically large.[8] This result is in line with the intuition that investors require a higher risk premium on stocks than bonds when market sentiment is low and a lower premium when the market sentiment is high (Laborda and Olma, 2014). Hence, there can be potential reallocation of portfolios by investors from distressed stocks to government bonds during the periods of low sentiment, thereby depressing the ex-post bond return because of the 'flight to quality' phenomenon (Nayak, 2010; Çepni and Guney, 2019).

– Insert Table 1 about here. –

Staying with further evidence of in-sample predictability from our new aligned investor sentiment index, in Figure 1 we plot excess bond returns of various maturities together with Inves.Sent.PLS index. Examination of these plots indicate that the PLS-based investor sentiment index tends to predict the turning points of 2-, 3-, 4-, and 5-year bond premia quite accurately.

– Insert Figure 1 about here. –

[8] In order to interpret the coefficient of sentiment indices, we scaled the projection coefficients by the standard deviation of the predictor variables so that they can be interpreted as the response to a one standard deviation move in the explanatory variable. For example, in Table 1, the coefficient of 0.176 for Inves.Sent.PLS index for 5-year bonds indicate that a one standard deviation change in investor sentiment is associated with a 166 basis points change in the 5-year bond risk premium.

Given the widely held view that the importance of variables and models should be judged based on out-of-sample validations, since in-sample predictability does not guarantee forecasting gains (Campbell, 2008), we now turn our attention to the forecasting exercises. Table 2 presents the out-of-sample forecasting results based on alternative model specifications. Models that yield the lowest mean squared forecast error (MSFE) values at each horizon are denoted in bold. We observe that the MSFEs generally increase with the forecast horizon. Also, virtually all of the entries in Table 2 are less than unity, indicating that alternative specifications based on predictors, especially CP, F_s, and the two sentiment indexes generally produce better forecasts than the benchmark RW model. In particular, comparing various model specifications, we find that the model that includes the CP, F_s and the Inves.Sent.PLS index always provides the lowest MSFEs, and attains the top rank in all of the cases, with it even outperforming the alternative model specification that comprise of the traditional Inves.Sent.BW sentiment index. Hence, the Inves.Sent.PLS index contain relevant information for predictability of excess bond returns. This observation is further supported by the predictive accuracy test of Harvey et al., (1997), which in turn implies statistically significant improvements in forecast accuracy compared to the RW model, at all horizons for bond premia of maturities of 2- and 3-year, and for certain short- and long-horizons (i.e., h = 1, 2, and 12) for the 4-year excess bond returns.

– Insert Table 2 about here. –

We also compared the results of the predictive accuracy test of Harvey et al., (1997) across the models that contain the information from the two alternative investor sentiment indexes, i.e., where RW+CP+F_s+Inves.Sent.BW model is selected as a benchmark. The p-values are reported in Table A1 in the Appendix of the paper, and as can be seen, the model with Inves.Sent.PLS statistically outperforms the model based on Inves.Sent.BW in a consistent fashion at all horizons and for all the four maturities of excess bond returns.

Our results validate that investor sentiment, especially when based on the PLS approach that exploits more efficiently the information in the proxies than the PCA procedure, contains significant predictive information, particularly for shorter-maturity bonds and shorter forecast horizons, as the MSFE values generally increase with the maturity of the bonds. This observation is further supported by the predictive accuracy test of Harvey et al., (1997), implying that the significance of forecast accuracy deteriorates for longer maturity bonds and longer forecast horizons. From an intuitive perspective, our results that investor sentiment captures significant predictive information, particularly for shorter-maturity bonds and shorter forecast horizons, is possibly an indication of short-term funding concerns during turbulent periods. At

the same time, the relative underperformance of investor sentiment as a predictor for longer maturities and forecast horizons might reflect possible mean reversion in investor sentiment and/or biases in the long-term risk outlook.

Furthermore, as part of alternative robustness checks, we extended our model by adding the investor attention or the augmented investor attention indexes of Chen et al., (2019) as an additional control in the predictive regressions, besides the Inves.Sent.PLS index, along with CP and F_s factors. Our findings in Table 3 show that combining the investor attention indexes does not improve the forecasting performance compared to the model that includes Inves.Sent.PLS index.

– Insert Table 3 about here. –

As discussed at length by Bai and Ng (2008), Kuzin et al., (2011, 2013), Stock and Watson (2012), and Kim and Swanson (2014, 2018), it is crucial to select appropriate predictors prior to estimation of predictive regressions. The reason behind this is that model and parameter uncertainty may adversely impact the marginal predictive content of explanatory variables. For this reason, as an additional robustness check, we analyze alternative variable selection methods namely, the Elastic-Net, the Least Absolute Shrinkage Operator (LASSO), and the Ridge regression in order to pre-select predictors prior to the constructing predictions. Accordingly, for each month, we choose indicators from the set of variables which includes CP, the Inves.Sent.PLS index and all the nine factors of Ludvigson and Ng (2009, 2011), instead of one combined factor F_s. As reported in Table 4, the model that includes the CP, F_s and Inves.Sent.PLS index retains its superiority in terms of out-of-sample forecasting, with the exceptions of bond premia forecasts from the Ridge regression at short- to medium-run horizons for the maturities of 2-, 3-, and 4-year in particular.[9]

– Insert Table 4 about here. –

Finally, in the Appendix of the paper, we conduct an additional econometric analysis to check for the robustness of our results by adding a manager sentiment index (Manager.Sent) as an additional control in

[9]However, if we applied the ridge regression by dropping the Inves.Sent.PLS index from the list of predictors, the performance of the Ridge regression is worsened to the extent that the RW+CP+F_s+Inves.Sent.PLS model outperforms this version of the ridge regression for excess bond returns of all maturities and horizons, with the exception of the 2-year bond premia at all horizons. This result suggests that while the Ridge regression approach is important, but more so is our aligned investor sentiment index incorporated into this framework. Complete details of these results are available upon request from the authors.

the predictive regressions, besides the CP, F_s and the Inves.Sent.PLS index. In this regard, we use the manager sentiment index of Jiang et al., (2019), who develops the index based on the aggregated textual tone of corporate financial disclosures, where textual tone is measured as the difference between the number of positive and negative words in the disclosure scaled by the total word count of the disclosure.[10] Jiang et al., (2019) found that Manager.Sent to be a strong (negative) in-sample and out-of-sample predictor of future stock market returns. To explore the predictive ability of the manager sentiment index for the excess bond returns, we repeat the our forecasting experiment. Given that Manager.Sent is available over 2003:01 to 2014:12, we utilize a recursive out-of-sample forecasting exercise over 2007:01 to 2014:12, given an in-sample of 2003:01 to 2006:12. As can be seen from the out-of-sample results in Table A2, the superiority of the model that includes the CP, F_s and Inves.Sent.PLS index continues to hold even in the presence of the manager sentiment index (with or without the investor attention indexes).

Overall, our findings of strong predictive power of the aligned investor sentiment for excess bond returns builds on and improves the work of Laborda and Olmo (2014), whose sentiment index was based on PCA, and is shown to be outperformed by our analysis, even after controlling for standard predictors and other types of investor attention and sentiment indexes used in the literature.

4. Conclusion

In this paper, we develop a new investor sentiment index aligned for predicting the bond premia of maturities of 2-, 3-, 4-, and 5-year of the US by applying the PLS approach to aggregate the information contained in the widely used six proxies of Baker and Wurgler (2006, 2007). We find that this new investor sentiment index has much greater predictive power for the excess bond returns, relative to the traditional investor sentiment index, which was derived based on PCA. More importantly, both in- and out-of-sample predictability is found to be statistically significant, especially for bond premia with shorter (i.e., 2-, 3-, and to some extent for 4-year) maturities, even after controlling for a large number of financial and macro factors, as well as investor attention and manager sentiment indexes commonly associated with asset market movements. Intutively, the success of the aligned investor sentiment is due to the use of the PLS approach that exploits more efficiently the information in the proxies than the PCA procedure. Hence, the aligned investor sentiment can achieve substantial improvements in forecasting US bond premia.

[10] The data is available for download from the website of Professor Guofu Zhou at: http://apps.olin.wustl.edu/faculty/zhou/.

One the one hand, the role of Treasury securities of the US as a global safe haven, primarily due to the significant lack of default risk, is well-established (Kopyl and Lee, 2016; Habib and Stracca, 2017; Hager, 2017). On the other hand, the yields on short and long-term Treasuries can capture valuable information regarding the current and future states of the economy and inflation (Plakandaras et al., 2017a; b; 2019). Hence, our results have significant implications for investors, policymakers and researchers interested in accurately forecasting return dynamics for these assets. Specifically speaking, the finding that investor sentiment, and in particular the new version based on PLS, affects the evolution of future interest rates can help policymakers in fine-tuning monetary policy. Bond investors can improve investment strategies by exploiting the role of the aligned investor sentiment index for interest-rate predictability, over and above the information derived from large number of macroeconomic and financial predictors summarized into common factors, and investor attention and manager sentiment indexes. In addition, researchers may find our results useful for developing better asset-pricing models that entirely use the information embedded in PLS-based estimates of investor sentiment.

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Table 1: In-sample regressions of monthly excess bond returns on predictors

Model: $rx_{t+1}^{(n)} = \alpha_0 + \beta' Z_t + \varepsilon_{t+1}$

		CP	F_s	*Inves.Sent.BW*	*Inves.Sent. PLS*	R^2
	(1)	0.38***				0.25
		(0.059)				
	(2)	0.14***	0.45***			0.48
		(0.046)	(0.054)			
$rx_{t+1}^{(2)}$	(3)	0.16***	0.43***	0.003**		0.50
		(0.047)	(0.054)	(0.001)		
	(4)	0.11**	0.458***		0.056**	0.50
		(0.047)	(0.058)		(0.024)	
	(1)	0.73***				0.25
		(0.111)				
	(2)	0.28***	0.85***			0.47
		(0.09)	(0.106)			
$rx_{t+1}^{(3)}$	(3)	0.30***	0.83***	0.003		0.48
		(0.09)	(0.107)	(0.003)		
	(4)	0.23**	0.844***		0.100**	0.49
		(0.093)	(0.114)		(0.052)	
	(1)	0.99***				0.24
		(0.16)				
	(2)	0.40***	1.132***			0.44
		(0.137)	(0.137)			
$rx_{t+1}^{(4)}$	(3)	0.41***	1.122***	0.001		0.44
		(0.137)	(0.151)	(0.004)		
	(4)	0.33**	1.127***		0.142*	0.45
		(0.145)	(0.161)		(0.08)	
	(1)	1.18***				0.22
		(0.203)				
	(2)	0.47***	1.347***			0.40
		(0.175)	(0.182)			
$rx_{t+1}^{(5)}$	(3)	0.47***	1.349***	-0.000		0.40
		(0.175)	(0.182)	(0.005)		
	(4)	0.38**	1.335***		0.176*	0.41
		(0.186)	(0.197)		(0.011)	

The table reports the estimates from OLS regressions of excess bond returns on the variables in columns. For example, the first row in panel $rx_{t+1}^{(2)}$ reports the results from the predictive model that includes only the CP factor. A constant is always included in the regressions. Standard errors are reported in parentheses. Entries superscripted with an asterisk denote the statistical significance (*** p < 0.01, ** p < 0.05, * p <0.1).

Table 2: Out-of-sample forecasting of excess bond returns based on alternative model specifications

$rx_{t+1}^{(2)}$	h=1	h=2	h=3	h=6	h=9	h=12
RW	0.011	0.011	0.011	0.011	0.011	0.011
RW+CP	1.026	1.037	1.043	1.052	1.052	1.045
RW+CP+F_s	0.847*	0.851*	0.854*	0.859	0.859	0.854
RW+CP+F_s+Inves.Sent.BW	0.829**	0.834*	0.839*	0.846*	0.848*	0.845*
RW+CP+F_s+Inves.Sent.PLS	**0.803****	**0.807****	**0.810****	**0.816***	**0.815***	**0.809****
$rx_{t+1}^{(3)}$						
RW	0.022	0.022	0.022	0.022	0.022	0.022
RW+CP	1.018	1.028	1.034	1.040	1.037	1.025
RW+CP+F_s	0.845*	0.847*	0.850*	0.854*	0.850*	0.840*
RW+CP+F_s+Inves.Sent.BW	0.859*	0.865*	0.871*	0.880	0.881	0.873
RW+CP+F_s+Inves.Sent.PLS	**0.817****	**0.820****	**0.824****	**0.830***	**0.826***	**0.814****
$rx_{t+1}^{(4)}$						
RW	0.031	0.030	0.030	0.030	0.030	0.030
RW+CP	1.045	1.057	1.063	1.069	1.064	1.052
RW+CP+F_s	0.896	0.900	0.904	0.908	0.905	0.894
RW+CP+F_s+Inves.Sent.BW	0.918	0.927	0.934	0.945	0.945	0.938
RW+CP+F_s+Inves.Sent.PLS	**0.871***	**0.876***	**0.881**	**0.889**	**0.885**	**0.872***
$rx_{t+1}^{(5)}$						
RW	0.039	0.039	0.039	0.039	0.039	0.039
RW+CP	1.047	1.057	1.062	1.066	1.061	1.048
RW+CP+F_s	0.921	0.925	0.928	0.932	0.929	0.918
RW+CP+F_s+Inves.Sent.BW	0.939	0.948	0.955	0.966	0.966	0.958
RW+CP+F_s+Inves.Sent.PLS	**0.899**	**0.906**	**0.911**	**0.920**	**0.916**	**0.903**

Entries in the first row of the table are point MSFEs based on the benchmark random walk (RW) model, while the rest are relative MSFEs. Hence, a value of less than unity indicates that a particular model and estimation method is more accurate than that based on the RW model, for a given forecast horizon. Models that yield the lowest MSFE for each forecast horizon are denoted in bold. Entries superscripted with an asterisk (** = 5% level; * = 10% level) are significantly superior than the RW model, based on the predictive accuracy test of Harvey et al., (1997).

Figure 1: PLS-based investor sentiment index and excess bond returns across maturities

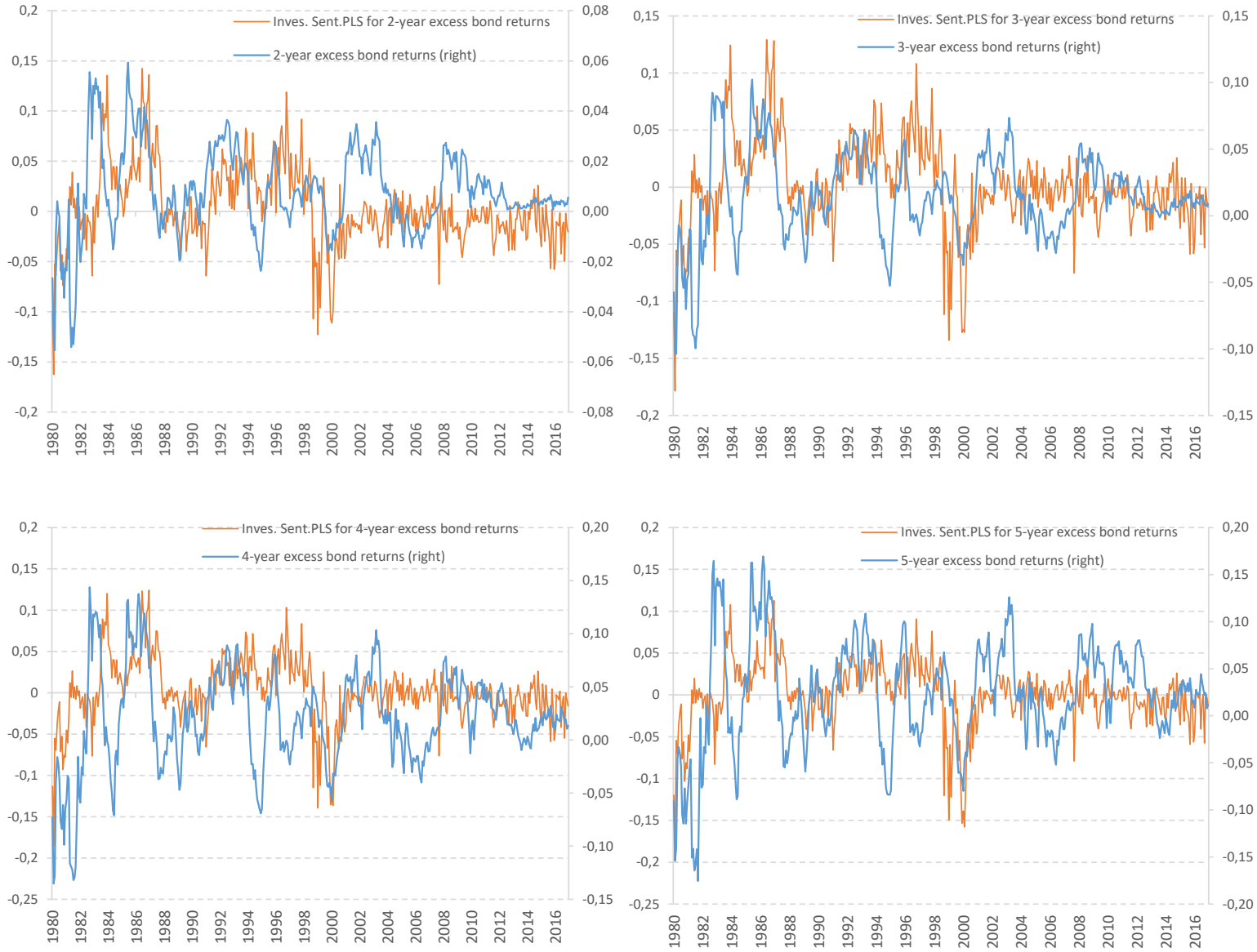

Table 3: Out-of-sample forecasting of excess bond returns by including information on investor attention

$rx_{t+1}^{(2)}$	h=1	h=2	h=3	h=6	h=9	h=12
RW	0.011	0.011	0.011	0.011	0.011	0.011
RW+CP+F_s+Inves.Sent.PLS	**0.803****	**0.807****	**0.810****	**0.816***	**0.815***	**0.809****
RW+CP+F_s+Inves.Sent.PLS+Inves.Att.	0.819**	0.827*	0.833*	0.844*	0.843*	0.833*
RW+CP+F_s+Inves.Sent.PLS+Inves.Att.Aug	0.816**	0.824*	0.830*	0.840*	0.839*	0.830*
$rx_{t+1}^{(3)}$						
RW	0.022	0.022	0.021	0.022	0.022	0.022
RW+CP+F_s+Inves.Sent.PLS	**0.817****	**0.820****	**0.824****	**0.830***	**0.826***	**0.814****
RW+CP+F_s+Inves.Sent.PLS+Inves.Att.	0.840*	0.850*	0.858*	0.870	0.866	0.847*
RW+CP+F_s+Inves.Sent.PLS+Inves.Att.Aug	0.842*	0.852*	0.858*	0.871	0.867	0.849*
$rx_{t+1}^{(4)}$						
RW	0.031	0.030	0.030	0.030	0.030	0.030
RW+CP+F_s+Inves.Sent.PLS	**0.871***	**0.876***	**0.881**	**0.889**	**0.885**	**0.872***
RW+CP+F_s+Inves.Sent.PLS+Inves.Att.	0.891	0.904	0.913	0.927	0.923	0.903
RW+CP+F_s+Inves.Sent.PLS+Inves.Att.Aug	0.901	0.912	0.921	0.935	0.931	0.912
$rx_{t+1}^{(5)}$						
RW	0.039	0.039	0.039	0.039	0.039	0.039
RW+CP+F_s+Inves.Sent.PLS	**0.899**	**0.906**	**0.911**	**0.920**	**0.916**	**0.903**
RW+CP+F_s+Inves.Sent.PLS+Inves.Att.	0.911	0.925	0.936	0.951	0.946	0.924
RW+CP+F_s+Inves.Sent.PLS+Inves.Att.Aug	0.927	0.940	0.949	0.963	0.959	0.938

Entries in the first row of the table are point MSFEs based on the benchmark random walk (RW) model, while the rest are relative MSFEs. Hence, a value of less than unity indicates that a particular model and estimation method is more accurate than that based on the RW model, for a given forecast horizon. Models that yield the lowest MSFE for each forecast horizon are denoted in bold. Entries superscripted with an asterisk (** = 5% level; * = 10% level) are significantly superior than the RW model, based on the predictive accuracy test of Harvey et al., (1997).

Table 4: Out-of-sample forecasting of excess bond returns based on variable selection methods

$rx_{t+1}^{(2)}$	h=1	h=2	h=3	h=6	h=9	h=12
RW	0.011	0.011	0.011	0.011	0.011	0.011
LASSO	0.837*	0.860	0.871	0.916	0.937	0.939
Elastic-Net	0.822**	0.846*	0.866	0.897	0.914	0.905
Ridge	**0.748*** **	**0.754*** **	**0.758*** **	**0.766** **	**0.765** **	**0.760** **
RW+CP+Fs+Inves.Sent.PLS	0.803**	0.807**	0.810**	0.816*	0.815*	0.809**
$rx_{t+1}^{(3)}$						
RW	0.022	0.022	0.021	0.022	0.022	0.022
LASSO	0.903	0.927	0.974	1.028	1.052	1.067
Elastic-Net	0.864	0.902	0.923	0.992	1.012	1.025
Ridge	**0.808*** **	**0.812** **	**0.816** **	**0.827** **	0.827**	0.819**
RW+CP+Fs+Inves.Sent.PLS	0.817**	0.820**	0.824**	0.830*	**0.826* **	**0.814** **
$rx_{t+1}^{(4)}$						
RW	0.031	0.030	0.030	0.030	0.030	0.030
LASSO	0.997	1.054	1.085	1.164	1.184	1.205
Elastic-Net	0.956	0.999	1.038	1.120	1.144	1.120
Ridge	**0.865** **	**0.871** **	**0.876** **	**0.889* **	0.891*	0.885*
RW+CP+Fs+Inves.Sent.PLS	0.871*	0.876*	0.881	0.889	**0.885**	**0.872* **
$rx_{t+1}^{(5)}$						
RW	0.039	0.039	0.039	0.039	0.039	0.039
LASSO	1.032	1.094	1.136	1.223	1.260	1.291
Elastic-Net	1.003	1.069	1.095	1.183	1.209	1.205
Ridge	0.899**	0.908**	0.914*	0.930	0.931	0.926
RW+CP+Fs+Inves.Sent.PLS	**0.899**	**0.906**	**0.911**	**0.920**	**0.916**	**0.903**

Entries in the first row of the table are point MSFEs based on the benchmark random walk (RW) model, while the rest are relative MSFEs. Hence, a value of less than unity indicates that a particular model and estimation method is more accurate than that based on the RW model, for a given forecast horizon. Models that yield the lowest MSFE for each forecast horizon are denoted in bold. Entries superscripted with an asterisk (*** = 1% level;** = 5% level; * = 10% level) are significantly superior than the RW model, based on the predictive accuracy test of Harvey et al., (1997).

Appendix

Table A1: Predictive accuracy test results across the models with alternative investor sentiment indexes

$rx_{t+1}^{(2)}$	h=1	h=2	h=3	h=6	h=9	h=12
RW+CP+F_s+Inves.Sent.BW	0.009	0.009	0.009	0.010	0.010	0.010
RW+CP+F_s+Inves.Sent.PLS	**0.969***	**0.968***	**0.966***	**0.965***	**0.961***	**0.957***
$rx_{t+1}^{(3)}$						
RW+CP+F_s+Inves.Sent.BW	0.019	0.019	0.019	0.019	0.019	0.019
RW+CP+F_s+Inves.Sent.PLS	**0.951****	**0.948****	**0.946****	**0.943****	**0.938****	**0.932****
$rx_{t+1}^{(4)}$						
RW+CP+F_s+Inves.Sent.BW	0.028	0.028	0.028	0.029	0.029	0.028
RW+CP+F_s+Inves.Sent.PLS	**0.948***	**0.945***	**0.943***	**0.941***	**0.936****	**0.930****
$rx_{t+1}^{(5)}$						
RW+CP+F_s+Inves.Sent.BW	0.037	0.037	0.037	0.038	0.038	0.037
RW+CP+F_s+Inves.Sent.PLS	**0.957***	**0.955***	**0.954***	**0.952***	**0.949***	**0.943***

Entries in the first row of the table are point MSFEs based on the model that includes CP, F_s and Inves.Sent.BW, while the rest are relative MSFEs. Hence, a value of less than unity indicates that a model with CP, F_s and Inves.Sent.PLS is more accurate than the CP, F_s and Inves.Sent.BW, for a given forecast horizon. Models that yield the lowest MSFE for each forecast horizon are denoted in bold. Entries superscripted with an asterisk (** = 5% level; * = 10% level) are significantly superior than the benchmark model, based on the predictive accuracy test of Harvey et al., (1997).

Table A2: Out-of-sample forecasting of excess bond returns by including information on manager sentiment index

$rx_{t+1}^{(2)}$	h=1	h=2	h=3	h=6	h=9	h=12
RW+CP+F_s+Inves.Sent.PLS	0.009	0.009	0.010	0.010	0.010	0.010
RW+CP+F_s+Inves.Sent.PLS+Manager.Sent	1.049	1.072	1.091	1.159	1.214	1.244
RW+CP+F_s+Inves.Sent.PLS+ Manager.Sent+Inves.Att	1.056	1.098	1.127	1.195	1.248	1.263
RW+CP+F_s+Inves.Sent.PLS+ Manager.Sent+Inves.Att.Aug	1.096	1.135	1.160	1.272	1.416	1.545
$rx_{t+1}^{(3)}$						
RW+CP+F_s+Inves.Sent.PLS	0.019	0.019	0.020	0.020	0.020	0.020
RW+CP+F_s+Inves.Sent.PLS+Manager.Sent	1.057	1.077	1.092	1.150	1.200	1.219
RW+CP+F_s+Inves.Sent.PLS+ Manager.Sent+Inves.Att	1.052	1.093	1.121	1.180	1.225	1.222
RW+CP+F_s+Inves.Sent.PLS+ Manager.Sent+Inves.Att.Aug	1.112	1.149	1.172	1.273	1.411	1.521
$rx_{t+1}^{(4)}$						
RW+CP+F_s+Inves.Sent.PLS	0.029	0.030	0.030	0.031	0.032	0.032
RW+CP+F_s+Inves.Sent.PLS+Manager.Sent	1.044	1.060	1.071	1.112	1.149	1.161
RW+CP+F_s+Inves.Sent.PLS+ Manager.Sent+Inves.Att	1.011	1.045	1.069	1.110	1.144	1.138
RW+CP+F_s+Inves.Sent.PLS+ Manager.Sent+Inves.Att.Aug	1.094	1.124	1.143	1.220	1.331	1.414
$rx_{t+1}^{(5)}$						
RW+CP+F_s+Inves.Sent.PLS	0.038	0.040	0.041	0.042	0.043	0.043
RW+CP+F_s+Inves.Sent.PLS+Manager.Sent	1.032	1.043	1.051	1.079	1.106	1.114
RW+CP+F_s+Inves.Sent.PLS+ Manager.Sent+Inves.Att	0.974	1.004	1.024	1.050	1.073	1.065
RW+CP+F_s+Inves.Sent.PLS+ Manager.Sent+Inves.Att.Aug	1.075	1.099	1.114	1.172	1.262	1.323

Entries in the first row of the table are point MSFEs based on the RW+CP+F_s +Inves.Sent.PLS model, while the rest are relative MSFEs. Hence, a value of less than unity indicates that a particular model and estimation method is more accurate than that based on the RW model, for a given forecast horizon. Models that yield the lowest MSFE for each forecast horizon are denoted in bold. Entries superscripted with an asterisk (** = 5% level; * = 10% level) are significantly superior than the RW model, based on the predictive accuracy test of Harvey et al., (1997). Due to the data availability of manager sentiment index, we utilize a recursive out-of-sample forecasting exercise over 2007:01 to 2014:12, given an in-sample of 2003:01 to 2006:12.