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Time-Varying Risk Aversion and the Predictability of Bond Premia

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Time-Varying Risk Aversion and the Predictability of Bond Premia

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We show that time-varying risk aversion captures significant predictive information over excess returns on U.S. government bonds even after controlling for a large number of financial and macro factors. Including risk aversion improves the predictive accuracy at all horizons (one- to twelve-months ahead) for shorter maturity bonds and at shorter forecast horizons (one- to three-months ahead) for longer maturity bonds. Given the role of Treasury securities in economic forecasting models and portfolio allocation decisions, our findings have significant implications for investors, policy makers and researchers interested in accurately forecasting return dynamics for these assets.

JEL classification: C22; C53; G12; G17

Keywords: Bond premia; Predictability; Risk aversion; Out-of-sample forecasts

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1. Introduction

The role of U.S. Treasury securities as a global safe haven is well established (e.g. Kopyl and Lee, 2016; Habib and Stracca, 2017), partially due to the significant lack of default risk fueled by the vast revenue stream the U.S. government generates, accounting for over 20 percent of global output. While the yields on short and long-term Treasuries can capture valuable information regarding the current and future states of the economy (e.g., Hamilton and Kim, 2002), return dynamics in these securities also reflect changes in risk perception among investors, particularly during periods of market stress when investors' risk appetite turns sour. Given the significance of Treasury securities both in economic forecasting models as well as portfolio allocation decisions, a massive and burgeoning literature exists on forecasting excess returns of U.S. government bonds (e.g. Cochrane and Piazzesi 2005; Ludvigson and Ng 2009, 2011; Gargano et al. 2017; Ghysels et al. 2018). 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.

Adopting a behavioral approach, Laborda and Olmo (2014) show that investor sentiment possesses significant predictive power over bond risk premia beyond that contained in the yield curve and benchmark macroeconomic factors, while Baker and Wurgler (2012) suggest that bonds and bond-like stocks exhibit similar predictability patterns driven by shocks to cash flows as well as fluctuations in investor sentiment. Motivated by these studies and considering the role of Treasury securities as a safe haven during periods of market turbulence, this paper explores the predictive power of risk aversion over Treasury bond premia by utilizing a new measure of time-varying risk aversion developed by Bekaert et al. (2017). The measure of risk aversion used as a predictor in our tests is obtained from observable financial information and distinguishes time variation in economic uncertainty (the amount of risk) from time variation in risk aversion (the price of risk), thus allowing us to explore the predictive ability of non-cash flow shocks over bond premia, even after controlling for the well-cited CP factor, and a large number of macro and financial factors (Ludvigson and Ng 2009, 2011). To the best of our knowledge, this is the first attempt to forecast excess returns on U.S. government bonds based on risk aversion.

Utilizing a linear predictive regression framework to forecast excess returns on two- to five-year government bonds, we show that time-varying risk aversion indeed has significant in- and out-of-sample predictive power over excess bond returns, even after controlling for a large number of financial and macro factors.

While the predictive value of risk aversion is particularly notable for shorter maturity bonds at all forecast horizons, we also observe that including risk aversion as a predictor improves the forecast accuracy for longer maturity bonds at short forecast horizons up to 3 months. We argue that risk aversion captures short-term liquidity concerns during turbulent market periods as well as investors' short-term protective trades via options. Our findings highlight the role of discount rate factors as a significant predictor of excess bonds returns with significant implications for investors and policy makers. The remainder of the paper is organized as follows. Section 2 provides data description and methodology. Section 3 presents empirical results and Section 4 concludes.

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).[1] 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 $t+1$. Depending on the model specification, Z_t includes the single forward factor (CP) of Cochrane and Piazzesi (2005)[2], the macro factors (LN) constructed by Ludvigson and Ng (2009, 2011) using dynamic factor analysis,[3] and the risk-aversion (RA) measure developed by Bekaert et al. (2017)[4].

The time-varying risk aversion measure is computed using observable financial information based on a set of six financial instruments (term spread, credit spread, a detrended dividend yield, realized and risk-

[1] 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, $rx_{t+1}^{(n)} \equiv r_{t+1}^{(n)} - y_t^{(1)}$.

[2] 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: $CP_{t+1} = \gamma_0 + \gamma^T f_t$.

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

[4] Data obtained from Nancy R. Xu's website at: https://www.nancyxu.net/risk-aversion-index.

neutral equity returns variance and realized corporate bond return variance). Based on the availability of the *RA* data, our sample period runs from 1986:05 to 2016:12.

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 order to examine how much of the variation in excess bond returns can be explained by different factors, we first run in-sample regressions as shown in Eq.(1). We then conduct a recursive out-of-sample forecasting exercise from 1995:01 to 2016:12 (in-sample 1986:06 to 1994:12) in order to analyze the predictive accuracy of alternative model specifications by adding each explanatory variable to the random-walk (RW) model one at a time. 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. For each month, we produce a sequence of six h-month-ahead forecasts for $h = 1, 2, 3, 6, 9, 12$. Finally, we use the mean squared forecast error (MSFE) adjusted test of Clark and West (2007) in order to evaluate forecast performance (relative to the RW model).

3. Empirical Results

In-sample results reported in Table 1 show that a single linear combination of the factors (F_s) together with the CP factor explains 42%, 37%, 31%, and 25% of the variation in future excess bond returns for two-, three-, four-, and five-year maturities, respectively. We observe that the explanatory variables have statistically significant predictive power, consistently for bonds at all maturities, in line with Ludvigson and Ng (2009, 2011), confirming that the information contained in the CP and F_s factors combined significantly improves the predictability of excess bond returns.[5] We also observe in Table 1 positive and significant coefficient estimates for risk aversion, suggesting that risk aversion has predictive power beyond that contained

[5]Since bond premia data are available from 1953:06, so is the CP factor whereas the LN factor dates back to 1960:03. In additional tests using these longer samples, we find that the model with the CP factor (CP and F_s factors) have R^2 values of 0.36 (0.55), 0.35 (0.53), 0.33 (0.49), and 0.31 (0.46) for future excess bond returns at maturities $n = 2, 3, 4, 5$, respectively.

in the benchmark macro and yield curve predictors. Furthermore, the size of the estimated coefficients for risk aversion increases with maturity, possibly reflecting the liquidity concerns that is proxied by higher risk aversion, thus driving investors to demand higher compensation for longer maturity bonds.

– Insert Table 1 about here. –

Table 2 presents the out-of-sample forecasting results based on alternative model specifications. Models that yield the lowest MSFE values at each horizon are denoted in bold. We observe that the MSFE values generally increase with the forecast horizon, with almost all MSFEs less than unity, indicating that alternative specifications generally produce better forecasts than the benchmark RW model. This observation is further supported by the MSFE-adjusted test of Clark and West (2007), indicating statistically significant improvements in forecast accuracy compared to the RW model, at all forecast horizons.

Comparing various model specifications, we observe that the model that includes only the CP and F_s factors usually provides the lowest MSFEs at longer forecast horizons and for longer maturities, confirming the out-of-sample predictive power of macro factors and forward rates over excess bond returns. Interestingly, however, including risk aversion substantially improves the predictive performance at shorter forecast horizons, ($h = 1, 2, 3$). In fact, the model which includes RA along with the CP and F_s factors attains the top rank in 18 out of 24 cases, outperforming the alternative model specifications that include the benchmark predictors only. The predictive power of risk aversion is particularly notable for shorter maturity bonds for which supplementing the model with RA as a predictor yields the best MSFEs across all forecast horizons. The plots of actual excess bond returns along with forecasts at various forecast horizons based on the full model that includes CP, F_s, RA and a constant, presented in Figures 1 to 4, further show that the model tends to capture turning points even in periods of high volatility.

Laborda and Olmo (2014) associate low (high) investor sentiment periods with exceptionally high (low) investor risk aversion periods and argue that low sentiment signals future increases in interest rates that depress ex-post returns on long maturity bonds against the one year bond. However, our evidence suggests that risk aversion captures significant predictive information, particular for shorter-maturity bonds and shorter forecast horizons, possibly capturing short-term funding concerns during turbulent periods, rather than expectations on future interest rates. Furthermore, considering that the risk aversion measure, by construction, is highly correlated with the variance risk premium embedded in option prices (Bekaert et al. 2017), the finding that the forecasting performance of RA is largely limited to shorter forecast horizons may be related to investor's short-term protection strategies via relatively cheaper, short-term options, driving their prices higher (thus option implied volatility). On the other hand, the relative underperformance of risk aversion 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. In sum, our results highlight the role of time-varying risk aversion as a significant predictor of excess bond returns.

– Insert Table 2 about here. –

– Figures 1 to 4 about here. –

4. Conclusion

This paper shows that time-varying risk aversion possesses significant predictive value (both in- and out-of-sample) over excess returns on U.S. government bonds even after controlling for a large number of financial and macro factors. The predictive value of risk aversion is particularly notable over short forecast horizons and shorter-maturity bonds, possibly reflecting funding concerns during turbulent periods. The finding that risk aversion contains predictive information over the evolution of future interest rates can help policy makers to fine-tune their monetary policy models. Bond investors can improve investment strategies by exploiting the role of risk aversion in their interest-rate prediction models, while risk managers can develop asset allocation decisions conditional on the level of risk aversion in the marketplace. Finally, researchers may utilize our findings to explain deviations from asset-pricing models by embedding risk aversion in their pricing models.

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

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

		CP	F_s	RA	R^2
$rx_{t+1}^{(2)}$	(1)	0.299***			0.23
		(10.52)			
	(2)	0.129***	0.456***		0.42
		(4.42)	(10.89)		
	(3)	0.128***	0.447***	0.001*	0.43
		(4.39)	(10.65)	(1.69)	
$rx_{t+1}^{(3)}$	(1)	0.532***			0.20
		(9.61)			
	(2)	0.222***	0.832***		0.37
		(3.83)	(10.01)		
	(3)	0.219***	0.813***	0.002**	0.38
		(3.79)	(9.75)	(2.01)	
$rx_{t+1}^{(4)}$	(1)	0.695***			0.17
		(8.64)			
	(2)	0.297***	1.069***		0.31
		(3.43)	(8.61)		
	(3)	0.293***	1.042***	0.003*	0.32
		(3.39)	(8.35)	(1.88)	
$rx_{t+1}^{(5)}$	(1)	0.773***			0.13
		(7.51)			
	(2)	0.314***	1.234***		0.25
		(2.78)	(7.62)		
	(3)	0.308***	1.192***	0.004**	0.26
		(2.74)	(7.35)	(2.22)	

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. Robust 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	0.0117	0.0117	0.0117	0.0117	0.0117	0.0115
RW+CP	1.027***	1.031***	1.033***	1.038***	1.039***	1.037***
RW+CP+F_s	0.821***	0.823***	0.824***	0.831***	0.834***	0.833***
RW+CP+F_s+RA	**0.760*****	**0.766*****	**0.769*****	**0.785*****	**0.789*****	**0.788*****
$rx_{t+1}^{(3)}$						
RW	0.0230	0.0230	0.0230	0.0231	0.0230	0.0225
RW+CP	0.969***	0.971***	0.974***	0.976***	0.975***	0.967***
RW+CP+F_s	0.794***	0.794***	0.795***	0.800***	0.799***	0.792***
RW+CP+F_s+RA	**0.759*****	**0.764*****	**0.767*****	**0.783*****	**0.784*****	**0.780*****
$rx_{t+1}^{(4)}$						
RW	0.0331	0.0330	0.0331	0.0331	0.0330	0.0322
RW+CP	0.968***	0.970***	0.972***	0.973***	0.972***	0.962***
RW+CP+F_s	0.816***	0.817***	0.818***	**0.822*****	**0.820*****	**0.812*****
RW+CP+F_s+RA	**0.797*****	**0.804*****	**0.808*****	0.826***	0.828***	0.826***
$rx_{t+1}^{(5)}$						
RW	0.0427	0.0427	0.0428	0.0428	0.0426	0.0416
RW+CP	0.969***	0.971***	0.973***	0.973***	0.971***	0.961***
RW+CP+F_s	0.836***	0.837***	0.837***	**0.841*****	**0.838*****	**0.831*****
RW+CP+F_s+RA	**0.819*****	**0.827*****	**0.833*****	0.850***	0.853***	0.852***

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) are significantly superior than the RW model, based on the Clark and West (2007) predictive accuracy test.

Figure 1: Actual 2-year excess bond returns together with forecasts at horizons (h=1, 2, 3, 6, 9, 12) based on the model including $CPfactor$, F_s, RA and constant

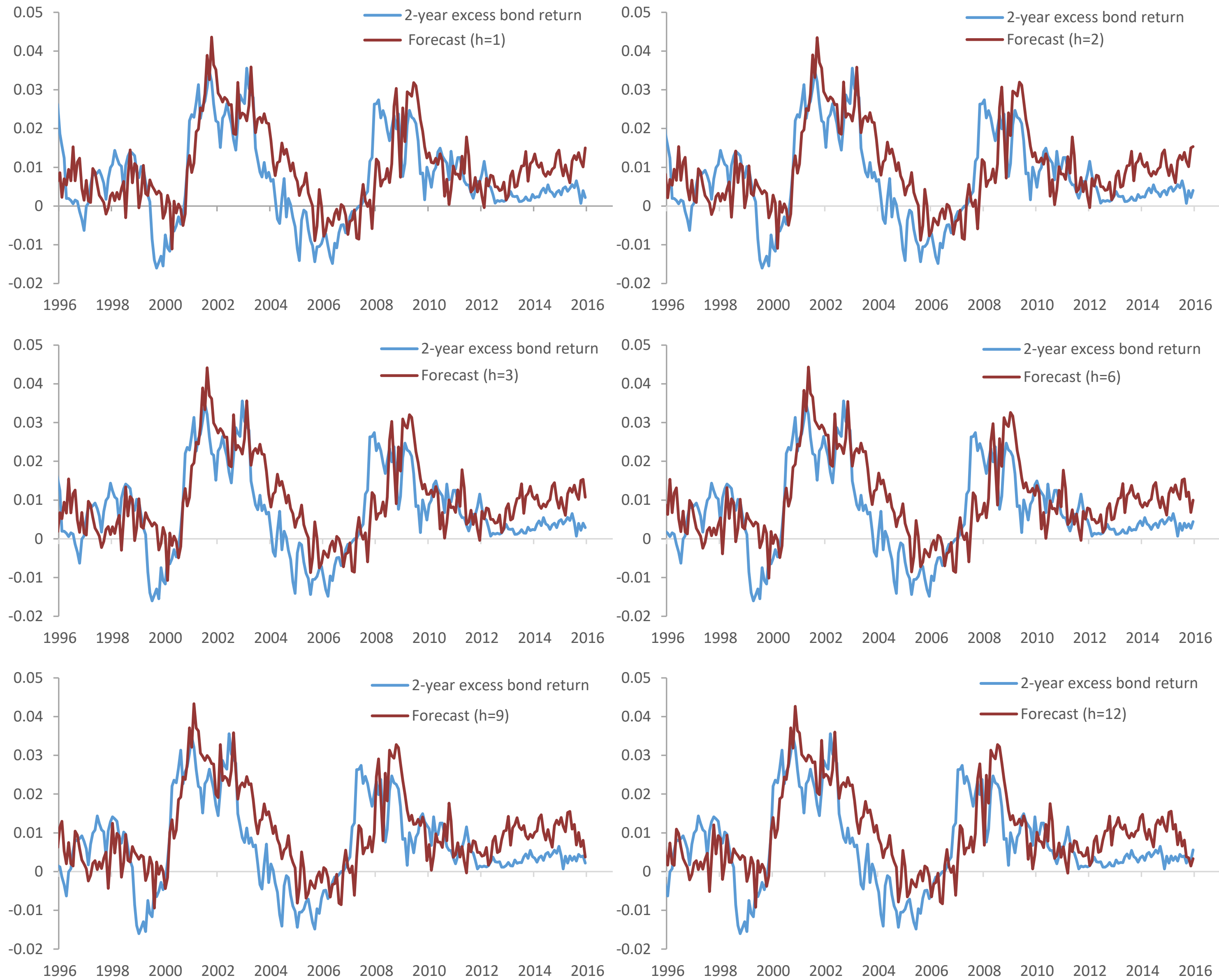

Figure 2: Actual 3-year excess bond returns together with forecasts at horizons (h=1, 2, 3, 6, 9, 12) based on the model including $CPfactor$, F_s, RA and constant

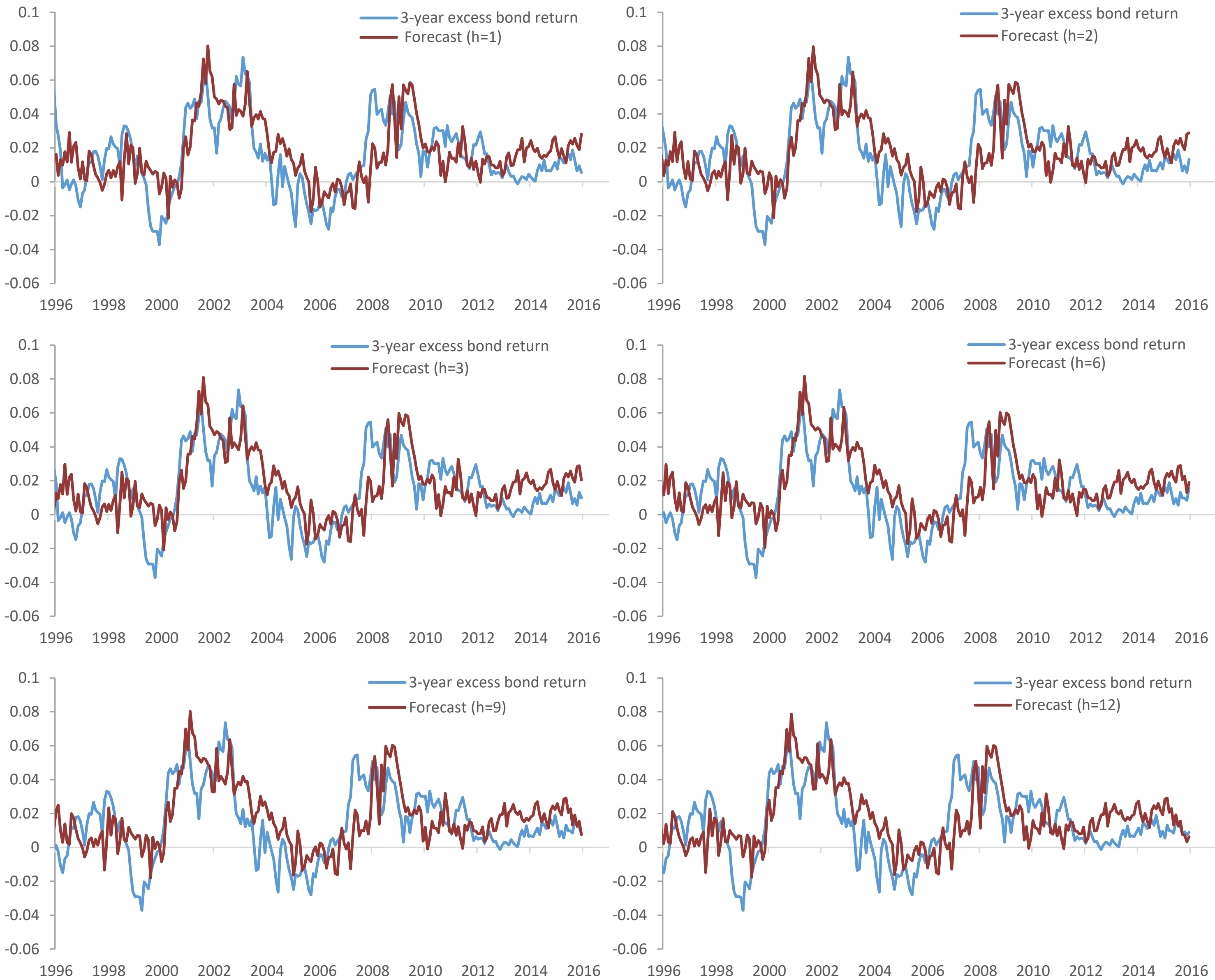

Figure 3: Actual 4-year excess bond returns together with forecasts at horizons (h=1, 2, 3, 6, 9, 12) based on the model including $CPfactor$, F_s, RA and constant

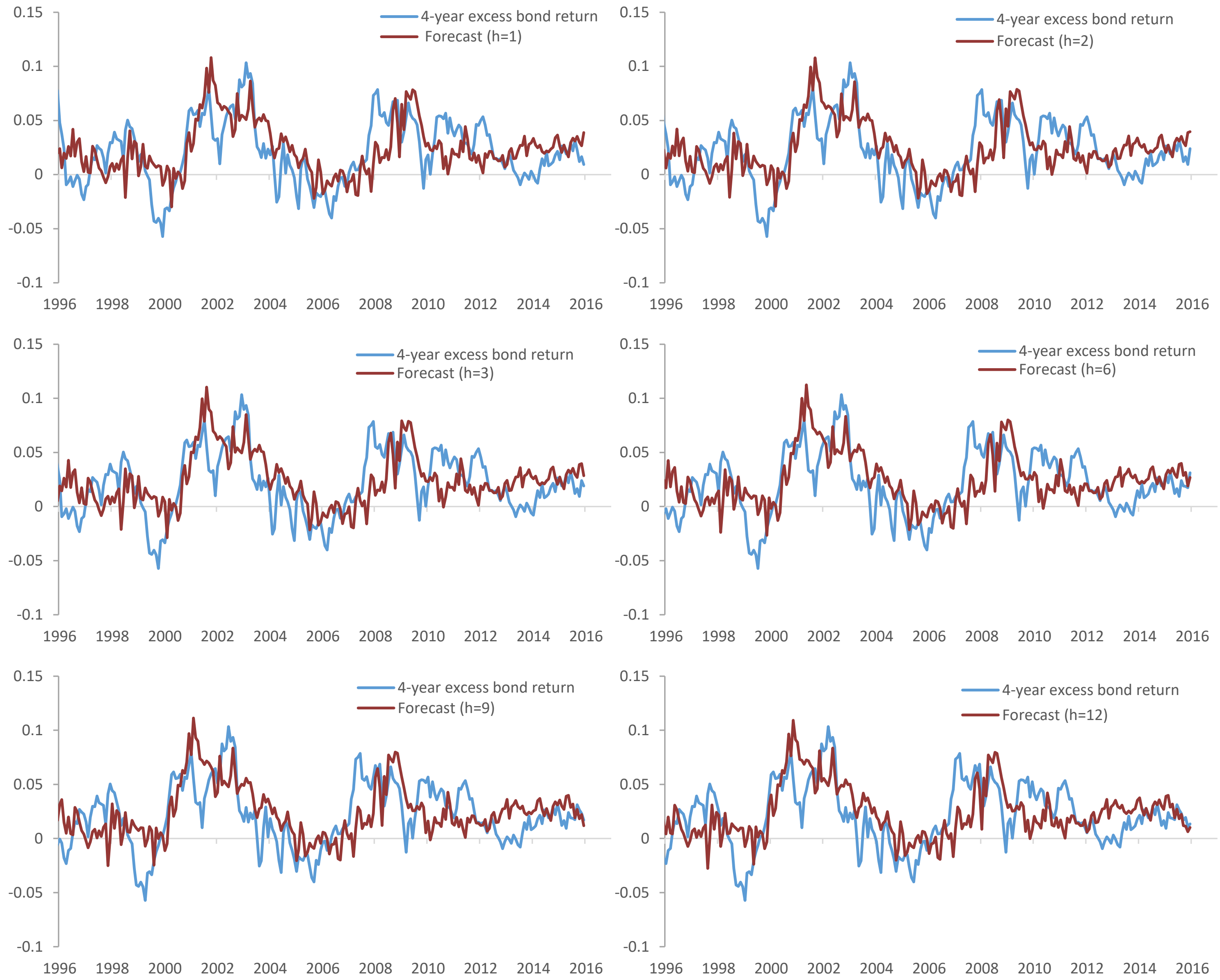

Figure 4: Actual 5-year excess bond returns together with forecasts at horizons (h=1, 2, 3, 6, 9, 12) based on the model including $CP factor$, F_s, RA and constant