International Review of Economics and Finance 46 (2016) 10–26

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Do economic variables improve bond return volatility forecasts?

Shih-Wei Chao

Department of Money and Banking, National Chengchi University, No.64, Sec.2, Zhinan Road, Taipei 116, Taiwan

ARTICLE INFO

Article history:
Received 23 March 2015
Received in revised form
24 November 2015
Accepted 9 August 2016
Available online 13 August 2016

JEL classification:
C22
G12
G17

Keywords:
Bond return volatility
Predictive ability
Forecast combination
Forecast performance decomposition

ABSTRACT

This paper explores whether various economic variables improve monthly bond return volatility forecasts using the 1963–2012 data. In-sample analysis indicates that stock return or Federal Funds rate difference Granger causes bond volatility of all maturities. The forecasting ability of other variables mainly appears at the short end of the term structure or during the relatively turbulent time. Out-of-sample analysis suggests little evidence of forecast improvement, though forecast combination does improve the performance. Decomposing the out-of-sample forecasts indicates that the poor performance is primarily attributed to overfitting, and variable reduction by principal components does not change the results.

1. Introduction

The average daily trading volume of the US Treasury securities is 545.4 billion dollars in 2013, which is 67% of the volume in all US bond markets and much greater than the 129.68 billion dollars for US stock markets.[1] As one of the largest financial markets in the world, its volatility has rich implications for portfolio evaluation, risk management and policy designation. Empirical analysis for the stock market suggests that return volatility is time-varying and thus more or less predictable. If some predictive relationship also exists in the US Treasury securities, this information would be valuable to bond market watchers. When forecasting bond return volatility, it would be important to investigate the role of macroeconomic and financial indicators for the following reasons. First, the investment decision of US Treasury securities is mostly affected by the macroeconomic condition. Thus the low-frequency variation of bond returns would be particularly important for long-term institutional investors since their decision is usually based on the trade-off between return and risk over a long horizon. Second, asset return volatility is usually high in recessions and periods of high inflation. If bond return volatility also displays a countercyclical pattern, business cycle drivers might contain useful information for predicting bond return volatility. Third, many asset pricing models emphasize the role of fundamentals in the dynamics of returns and risks. The empirical evaluation of the predictive relationship of economic variables and bond return volatility provides stylized facts to

E-mail address: swchao@nccu.edu.tw

[1] http://www.sifma.org/research/statistics.aspx.

http://dx.doi.org/10.1016/j.iref.2016.08.001

examine the empirical performance of these models. Finally, past studies of volatility comprehensively address the time series properties while left a minor role to the economic environment. As a result, how economic activities and financial indicators signal the dynamics of bond return volatility is still a question of interest.

This paper evaluates whether various economic variables significantly improve the monthly return volatility forecasts for the US Treasuries. Despite the importance of US Treasury markets, the link between low-frequency bond return volatility and the state of the economy receives relatively little attention. As a result, this paper makes at least two contributions to the literature. First, existing studies on bond return volatility prediction focus on a particular maturity or relatively short sample period. This study instead investigates a wide range of maturities, a relatively longer 1963–2012 sample and various specification of forecasting models. The results provide a more comprehensive picture of how the forecasting ability of various economic variables varies with bond maturity and over time. This study also evaluates the out-of-sample performance of several forecast combination schemes. The results would illuminate whether this method significantly reduces variation and bias for bond return volatility forecasts. Second, in-sample and out-of-sample prediction often reach different conclusions in the literature. Although the reliability of two approaches is not the focus of this study, understanding their discrepancy might shed light on how to improve the forecasting model. For example, if undesirable out-of-sample performance is due to changing forecasting ability over time, it would be important to investigate whether this instability is related to structural breaks in parameter estimates or variations of forecasting variables. If the problem is overfitting, excluding some less relevant predictors could lead to better results. This paper provides statistical evidence to identify the primary source of the difference between in-sample and out-of-sample bond return volatility forecasts.

Following Andersen, Bollerslev, Diebold, and Ebens (2001); Andersen, Bollerslev, Diebold, and Labys (2001, 2003), bond return volatility in this paper is measured by realized volatility, which is the sum of squared intra-period returns. The literature has established nice statistical properties for realized volatility under some regular conditions, so its prediction can be proceeded with simple econometric methods. The forecasting model is a linear predictive regression including appropriate lags of bond return volatility and various economic variables as regressors. Although many authors employ different versions of GARCH and successfully describe the salient facts of volatility, they are primarily interested in modeling the clustering, fat-tailed distribution and high-frequency variation of volatility. Because this paper focuses on the role of economic variables in predicting monthly bond return volatility, linear regression is a flexible framework for this purpose. The bond return volatility series are constructed from the CRSP Fixed Term Indices file. Forecasting variables include measures of output growth and its volatility, employment growth, inflation and its volatility, stock return and its volatility, stock market liquidity, default spread, long-short yield spread, and movements in risk-free rate and Federal Funds rate. The predictive regression nests the autoregressive specification as the benchmark when comparing volatility forecasts.

The analysis of the full sample period data indicates that stock return or movements in the Federal Funds rate Granger causes bond return volatility of various maturities. A decline in stock return or a rising Federal Funds rate predicts higher bond return volatility, while the significance decreases in bond maturity. Subsample results suggest that economic variables tend to improve the in-sample fit during relatively turbulent periods, such as sustained high inflation in the 1970s or a series of financial crisis during the late 1990s and early 2000s. The largest increment of R^2 relative to the benchmark is below 3%, which lacks impressive economic significance. On the other hand, the out-of-sample evaluation displays weaker evidence of forecasting ability. Most augmented models with economic variables do not beat the benchmark. In fact, some of these models produce very poor forecasts, particularly when the model contains a large number of predictors. Following Rapach, Strauss, and Zhou (2010), this paper also evaluates the out-of-sample performance of several forecast combination schemes. The results indicate that ensemble bond return volatility forecasts appear to outperform the benchmark in some circumstances. The null of equal predictive ability can be rejected in favor of smaller forecast errors for some combined forecasts for 1- and 10-year Treasuries. The combined forecasts also tend to perform better in the relatively unsettled periods, but the improvement of out-of-sample R^2 relative to the benchmark is below 2% .

To explain the difference between in-sample and out-of-sample forecasting performance, this study follows Rossi and Sekhposyan (2011) to decompose the out-of-sample mean forecast error into three asymptotically uncorrelated components, namely forecast instability, predictive content and overfitting. For those significantly worse volatility forecasts, the tests often rejects the null of no overfitting but fails to reject the null of no forecast instability or no lack of predictive content. To explore whether variable reduction is a remedy to this overfitting problem, the predictors are replaced by several principal components of these economic variables. Unfortunately, using these principal components rarely improves the out-of-sample performance relative to the benchmark. In sum, these economic variables provide little useful information in addition to the benchmark autoregression model when making out-of-sample bond return volatility forecasts, particularly for intermediate and long maturities.

This paper relates to the literature of the link between low-frequency bond return volatility and macroeconomic variables.[2] Christiansen, Schmeling, and Schrimpf (2012) explore the economic determinants of return volatility for a variety class of assets, including the 10-year Treasury Notes futures. The authors use Bayesian model averaging to determine the specification of forecasting models and rank the predictive ability of each model accordingly. Their results based on the

[2] A strand of literature provides evidence on the effects of macroeconomic news announcements on bond market volatility, such as Bollerslev, Caic, and Song (2000); Brenner, Pasquariello, and Subrahmanyam (2009); Jones, Lamont, and Lumsdaine (1998), among others. These studies mostly focus on analyzing high-frequency (intra-day or daily) variation of bond returns.