Bond Return Predictability and Macroeconomy: The International Link

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Abstract

This paper provides real-time out-of-sample evidence on the international link of macroeconomic risks for government bonds. Motivated by a simple production-based model, we construct a global macroeconomic factor (GMF) from a panel of international real-time macroeconomic variables that are not subject to future revisions or release delay. We find that the GMF, as an aggregate measure of world macro risks, predicts strongly bond risk premia across countries, with out-of-sample R^2 up to 23%. In contrast, a local macroeconomic factor (LMF) extracted from local macroeconomic variables generate mixed results. The predictive power of the GMF is robust after controlling the Cochrane-Piazzesi factor and the global forward-rate factor. Overall, its predictability is not only significant statistically, but also important economically. Moreover, the GMF also contains information for predicting international stock returns and carry trade profitability.

JEL Classifications: G1, E4, F3.

Keywords: Bond risk premia, economic value, global economic indicator, real-time macroeconomic factors, return predictability.

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1 Introduction

What economic fundamentals drive government bond returns? Theoretically, Piazzesi and Schneider (2006), Wachter (2006), Buraschi and Jiltsov (2007), and Jermann (2013), among others, provide insights into the role played by macroeconomic risks in bond risk premia. Empirically, substantial advances have been made to identify various variables, such as real economic activity (e.g., Joslin, Priebsch, and Singleton, 2014), inflation (e.g., Wright, 2011), principle components extracted from a large set of macro variables (Ludvigson and Ng, 2009), and expected business conditions (e.g., Eriksen, 2016), that can forecast bond returns and hence drive the bond risk premia. However, Thornton and Valente (2012) find that, out-of-sample, the existing variables have little predictability statistically, and there is no economic value of utilizing such predictability either. Sarno, Schneider, and Wagner (2016) reach a similar conclusion. Moreover, Ghysels, Horan, and Moench (2014) find that real-time macroeconomic variables have even less predictability than previously found because previous studies rely on macroeconomic data with delay or subject to revisions which can have a look-ahead bias and are unavailable to economic agents at the time of their decision making. In particular, Bauer and Hamilton (2016) and Bauer and Rudebusch (2016), in their re-examining of bond predictability, find that macroeconomic factors cannot robustly predict bond returns. Therefore, whether bond risk premia are changing or not with macroeconomic risks is still an open question.

In this paper, we resolve the open question. We propose a global macroeconomic factor (GMF) or predictor from a panel of international real-time macroeconomic variables, and show that it can predict country bond risk premia significantly both from statistical and economic perspectives. Unlike most studies, we emphasize the link of bond predictability across countries. This is not surprising given a global economy and the fact that bond investors are searching yields all over the globe. Theoretically, we also provide a simple model to motivate and justify the use of our GMF instead of a local macro factor (LMF) extracted from a set of local variables. In contrast to existing studies, our paper is the first to provide strong evidence on the real-time predictability of bond returns based on macroeconomic variables that are available in real-time.

In our paper, we focus on a world of the four largest and most liquid bond markets: the United States, the United Kingdom, Japan, and Germany, for which a panel of real-time macroeconomic variables are available. To extract information contained in a large panel of real-time macro variables, we use the partial least square (PLS, Wold, 1975, Kelley and Pruitt, 2013), which is a simple and more efficient method than the principle components approach in terms of pooling information for forecasting. In line with Ghysels, Horan, and Moench (2014), we find that the LMF for each country extracted from a panel of the real-time local variables even by using the PLS has weak predictive power out-of-sample for the bond risk premia of each country. In contrast, some studies, such as Ilmanen (1995) and Ludvigson and Ng (2009), find there are certain degrees of out-of-sample predictability of local macroeconomic variables on local bond risk premia. The key reason for the difference in the results is that we use the real-time available variables, and they do not.

Unlike LMF, the GMF is constructed via the PLS based on real-time macroeconomic variables of all the four countries. Hence, the GMF captures global macroeconomic risks rather than merely country ones. Because of this, we find that the GMF predicts strongly bond risk premia across countries, with out-of-sample R^2s as high as 23%. Further forecast encompassing analysis shows that the GMF's predictive ability encompasses the LMF's predictive power for US, UK, and Japan, suggesting the importance of global macro risks in bond pricing. Moreover, the GMF carries predictive power for future bond risk premia over and above the information contained in the forward-rate predictor of Cochrane and Piazzesi (2005), the risk-premium factor of Cieslak and Povala (2015), and the international term-structure factors (e.g., Ilmanen, 1995; Dahlquist and Hasseltoft, 2013, and Zhu, 2015). Overall, our strong empirical evidence suggests that it is the international macroeconomic risks rather domestic ones that are critically important for bond pricing. The implication of our paper is to call for new bond asset pricing models that incorporate both local and global macroeconomic risks in a unified framework.

Economically, our results are broadly consistent with Ludvigson and Ng (2009), Wright (2011) and Joslin, Priebsch, and Singleton (2014), who find that macroeconomic risks are unspanned by the term structure of interest rates. In particular, the results are consistent with Ilmanen (1995) and Dahlquist and Hasseltoft (2013) who suggest that global risks are important for understanding the time-variation in bond risk premia. Toward this end, we find marked countercyclical variation in the bond risk premia implied by the GMF, while the bond risk premia implied by the historical average are acyclical. These results are largely robust to additional analysis with in-sample forecasting and multiple-step-ahead forecasting. Moreover, we find interestingly that the US bond market does not play a leading role in the international bond markets, unlike the case of the equity market (Rapach, Strauss, and Zhou, 2013). That is perhaps due to less information friction in the bond market, which drives the lead/lag relation of the equity market, because bond traders are mostly professional traders and are more informed than the stock investors.

Our third set of results is related to the economic value of the GMF. In the spirit of Campbell and Thompson (2008) and Welch and Goyal (2008), we consider an asset allocation problem in which a mean-variance investor allocates his/her fund between a long-term bond and the one-year risk-free Treasury bill. In this case, the utility gain of predictability to the investor is the utility difference between two different investing strategies: the strategy of using the GMF to dynamically rebalance the bond portfolio and the strategy of using the expectation hypothesis (the historical average benchmark) to form bond portfolios. We find that the GMF consistently delivers positive economic values. The utility gains of using the GMF are, respectively, 1.67%, 2.01%, 0.04%, and 1.85% for the United States, the United Kingdom, Japan,and Germany. Overall, our evidence suggests that the GMF has economically and statistically important predictive power in forecasting international bond returns.

Is the international link of macroeconomic risks captured by the GMF unique to the bond market? Consider two other major financial markets, the stock market and the foreign exchange markets. Since a well-diversified global investor is likely to invest in all the three asset classes, there is intuitively a link of time-varying risk premia across the three financial markets. Indeed, we find that the GMF contains important information for predicting international stock returns above and beyond what is contained in country-specific LMFs. Moreover, in the spirit of Lustig, Roussanov, and Verdelhan (2011) and Bakshi and Panayotov (2013), we find that the GMF can also predict out-of-sample the carry trade premium. These results show further that the GMF measures pervasive economic risks that drive asset prices across all the markets.

In summary, we provide strong evidence on time-varying bond risk premia. In particular, we find that the GMF explains more time variation and provides significantly more accurate forecasts than the LMF. The enhanced bond predictability indicates that global macroeconomic risks are an important source of the time variation in expected bond returns. Our results have important implications for bond pricing models: ignoring international economic linkages can overstate the importance of domestic macroeconomic risks in pricing bonds and in explaining the time variation in bond risk premia. Our analysis thus suggests that one cannot simply price bonds within a country based on only its own country economic and term structure variables. Instead, our results call for an international bond pricing model that accounts explicitly for the global economic driving force of bond returns.

The remainder of the paper is organized as follows. In Section 2, we present a simple international production-based model that justifies GMF. Section 3 outlines the methodology for predicting bond returns. In Section 4, we report the out-of-sample predicting results of both LMF and GMF. Section 5 conducts various robustness checks. Section 6 investigates whether the U.S. plays a leading role in the international bond markets. Section 7 further studies the predictive power of the GMF on stock and currency returns. Section 8 concludes.

2 A Simple Production-Based Model

This section presents a simple production-based model that links between the production side of the economy and asset prices. Specifically, the model recovers a stochastic discount factor for asset returns from producer's first-order conditions and links asset returns to production. We build the model upon the neoclassical growth model and extend the approach in Balvers, Cosimano, and Mcdonald (1990), Belo (2010) and Cochrane (1991) by allowing the international diffusion of knowledge through global learning by doing. We want to emphasize that the ad hoc production-based model serves to illustrate the point of view that international economic linkages are important for asset pricing, but leave a more full-fledged general equilibrium for future research.

In the model, a home-country representative firm determines its level of investment each period to maximize firm value using the market-determinant stochastic discount factor to value its real cash flow. All cash flow is paid to shareholders in the form of dividends D_t. Dividends are measured as the difference between output, Y_t, and investment, I_t. Output is produced by a stochastic, decreasing returns, Cobb-Douglas technology with multiplicative, serially uncorrelated uncertainty, θ_t, such that $E(\theta_t) = 1$, and with capital, K_t, as the only input. For simplicity, capital is assumed to be depreciate fully each period. There is a gestation lag of one period before investment becomes productive as capital in the production function. Thus, current investment, I_t, is identical to next period's capital stock, K_{t+1}. The firm observes the current stochastic output shock θ_t, before it determines investment.

In our setting, technological progress in home country relies on international learning-by-doing. On the other hand, we assume that technological progress in the foreign country is a constant,[1] so the foreign output is

$$Y_t^* = a^* \theta_t^* K_t^*, \tag{1}$$

where θ_t^* is multiplicative, serially uncorrelated uncertainty such that $E(\theta_t^*) = 1$. We use the $*$ notation throughout to denote the foreign country. Markets are complete and thus the stochastic discount factor is unique. The producer uses this discount factor, M_t, to discount cash flow and and maximizes firm value:

$$E_0 \sum_{t=0}^{\infty} \left[\prod_{j=0}^{t} M_j \right] D_t \tag{2}$$

subject to

$$D_t = Y_t - I_t = Y_t - K_{t+1}, \tag{3}$$

$$Y_t = A_t \theta_t K_t^{\alpha},\ \alpha > 0, \tag{4}$$

where the learning-by-doing process is

$$A_t = a K_t^* K_t^{\beta} + b K_t^{\gamma},\ \beta > 0 \text{ and } \gamma > 0, \tag{5}$$

[1] This simplifies the analysis. If we set technological progress in the foreign country as a learning-by-doing process, we can find the similar implications for asset returns and production.

where a and b are constants. The first term on the right hand side capture the effect of international diffusion of knowledge through learning-by-doing (e.g., Young, 1991; Lucas, 1993), and the second term is a normal learning-by-doing process by using domestic capital. Substituting equation (1) into (5), we have

$$A_t = \frac{a}{a^* \theta_t^*} Y_t^* K_t^{\beta} + b K_t^{\gamma}. \tag{6}$$

Substituting equations (6), (3), and (4) into (2) and differentiating with respect to K_{t+1} deliver the stochastic Euler condition:

$$E_t[M_{t+1}(d_{1,t+1} Y_{t+1} + d_{2,t+1} Y_{t+1}^*)] = 1, \tag{7}$$

where $d_{1,t+1} = \frac{\alpha+\gamma}{K_{t+1}}$ and $d_{2,t+1} = (\beta - \gamma) a \theta_{t+1} K_{t+1}^{\alpha+\beta}$. Assuming that the stochastic discount factor and $(d_{1,t+1} Y_{t+1} + d_{2,t+1} Y_{t+1}^*)$ are jointly log-normal and let lowercase letters to denote logs of the corresponding variables throughout this section, it leads to

$$E_t(m_{t+1}) + d_1 E_t(y_{t+1}) + d_2 E_t(y_{t+1}^*) + \frac{1}{2} V_{t,1} = 0, \tag{8}$$

where $d_1 = E_t(d_{1,t+1}) = \frac{\alpha+\gamma}{I_t}$, $d_2 = E_t(d_{2,t+1}) = (\beta - \gamma) a I_t^{\alpha+\beta}$,[2] and $V_{t,1}$ is the conditional variance of the log of $M_{t+1}(d_{1,t+1} Y_{t+1} + d_{2,t+1} Y_{t+1}^*)$. Moreover, the standard Euler equation, $E_t[M_{t+1} R_{t+1}] = 1$, and the joint log-normal assumption also lead to

$$E_t(m_{t+1}) + E_t(r_{t+1}) + \frac{1}{2} V_{t,2} = 0, \tag{9}$$

where we define $V_{t,2}$ to be the conditional variance of the stochastic discount factor plus the asset return. Equations (8) and (9) imply that

$$E_t(r_{t+1}) = a + d_1 E_t(y_{t+1}) + d_2 E_t(y_{t+1}^*), \tag{10}$$

where $a = \frac{1}{2} V_{t,1} - \frac{1}{2} V_{t,2}$. Therefore, the expected log return is a function of both the domestic

[2] Note that θ_{t+1} is uncorrelated to Y_t and $K_{t+1} = I_t$ is observed at time t, so $d_{1,t+1}$ and $d_{2,t+1}$ are observed at time point t and uncorrelated to Y_{t+1} and Y_{t+1}^*.

economic condition, $E_t(y_{t+1})$, and the foreign economic condition, $E_t(y^*_{t+1})$. If the two-country model is extended to a multiple-country setting, it naturally implies that expected returns in home market are a function of global economic conditions. Furthermore, without the international diffusion of knowledge, the model implies that expected returns are solely a function of domestic economic indicator.

3 Empirical Methodology

In this section, we describe our empirical methodology. First, we introduce the PLS approach and the predictive regression framework. Then, we discuss the criteria for evaluating the accuracy of out-of-sample forecasts. Third, in the spirit of Welch and Goyal (2008) and Campbell and Thompson (2008), we discuss how to assess the economic value of predictive regressions. Finally, we introduce the forecast encompassing test.

3.1 The PLS method

The GMF and LMF are aligned factors extracted from a set of macroeconomic variables using the PLS approach. Let $Z_t = (z_{1,t}, z_{2,t}, \ldots, z_{N,t})$ denote an $N \times 1$ vector of a panel of real-time macro variables at period t, following Wold (1975) and Kelly and Pruitt (2013), we assume that $z_{i,t}$ has a factor structure

$$z_{i,t} = a_{i,0} + a_{i,1} MF_t + a_{i,2} ER_t + e_{i,t}, \tag{11}$$

where MF_t is the component related to future bond risk premia, and ER_t is the common component of all real-time macro variables that is irrelevant to returns, and $e_{i,t}$ is the idiosyncratic noise associated with factor i only. The PLS approach is to impose a factor structure on the proxies to efficiently estimate MF_t and to eliminate ER_t. Specifically, the PLS method use a two-step procedure to extract MF_t from macro variables. In the first step, for each individual macroeconomic variable i, we run a time-series regression of $z_{i,t}$ on a constant and excess return r_{t+1},

$$z_{i,t} = w_{i,0} + w_i r_{t+1} + u_{i,t},\ for\ i = 1, \ldots, N. \tag{12}$$

The loading w_i captures the sensitivity of $z_{i,t}$ to MF_t that predicts r_{t+1}.

In the second-step, for each forecast period t, we run a cross-sectional regression of $z_{i,t}$ on the corresponding loading $\hat{w}_i$ estimated in first-stage regression (12),

$$z_{i,t} = c_t + MF_t^{PLS} \hat{w}_i + v_{i,t},\ for\ t = 1, \ldots, T, \tag{13}$$

where MF_t^{PLS}, the regression coefficient in (13), is the aligned macro index. In estimation, if Z_t only includes local real-time macroeconomic variables, the filtered aligned factor is the local macro factor (LMF). Alternatively, if we use all macro factors for US, UK, German and Japan to filter out an aligned factor, this factor is labelled as the global macro factor (GMF). PLS uses expected returns to discipline the dimension reduction to filter out the aligned real-time macro factors that carry predictive power for future returns. Mathematically, as Kelly and Pruit (2013) indicate, the two-step procedure has a one-step representation. Let $MF^{PLS} = (MF_1^{PLS}, MF_2^{PLS}, \ldots, MF_T^{PLS})$, $Z = (z_1', z_2', \ldots, z_T')$, and R denotes the $T \times 1$ vector of asset returns as $R = (r_2, r_3, \ldots, R_{T+1})$, the one-step algorithm is

$$MF^{PLS} = Z J_N Z' J_T R (R' J_T Z J_N Z' J_T R)^{-1} R' J_T R, \tag{14}$$

where $J_L = I_L - \frac{1}{L} \iota_L \iota_L'$, I_L is the L-dimensional identity matrix, and ι_L is an L-vector of ones.

Because the first-stage regression takes an errors-in-variables form, second stage estimates of the latent expectations have a multiplicative bias. However, since OLS forecasts are invariant to affine transformations of regressors, a predictive regression of realized returns on the estimated factors delivers consistent estimates of expected returns.

Kelly and Pruitt (2012) demonstrate that this procedure is consistent: it asymptotically recovers the latent expectations of asset returns as the number of predictors and time-series observations both become large. Furthermore, they provide asymptotic distribution theory for the predictive coefficient under weak conditions. In particular, Kelly and Pruitt (2012) prove that this procedure remains consistent even if there are additional factors that drive the cross-section of macro variables but do not impact expected market returns or dividend growth.

3.2 Predictive regressions

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 $p_t^{(n)} = \ln P_t^{(n)}$ is the log bond price of the n-year zero-coupon bond at time t. A forward rate at time t for loans between time $t+n-1$ and $t+n$ is defined as

$$f_t^{(n)} \equiv p_t^{(n-1)} - p_t^{(n)}. \tag{15}$$

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

$$r_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)}. \tag{16}$$

Naturally, the risk premium on an n-year discount bond over a short-term bond is the difference between the holding period return of the n-year bond and the 1-period interest rate

$$rx_{t+1}^{(n)} \equiv r_{t+1}^{(n)} - y_t^{(1)}. \tag{17}$$

Following the vast literature, to assess whether excess bond returns are predictable, we run a standard predictive regression

$$rx_{t+1}^{(n)} = \alpha + \beta X_t + \varepsilon_{t+1}, \tag{18}$$

where X_t is the pre-determined predictor(s). If X_t is the GMF or LMF, we just run a predictive regression of realized bond returns on the aligned macroeconomic factors estimated in the second stage of the PLS approach.

Motivated by the international production-based model, this paper proposes to use the GMF as the predictors of the excess bond returns. The use of the GMF is also motivated by economic theories suggesting that rational economic agents should be compensated for bearing macroeconomic risks. For example, the classic work of Merton (1973) indicates that the state of the economy represents changing investment opportunities and drives time-varying risk premia. In term of bond risk premia, Buraschi and Jiltsov (2007) and Wachter (2006) link term structure dynamics to economic fundamentals and show that bond risk premia should vary with macroeconomic shocks. In a recursive utility framework, Piazzesi and Schneider (2007) suggest that investors may require a premium to hold nominal bonds due to the fear of stagflation. In the spirit of these equilibrium term structure models, we use LMF to predict excess bond returns. While it is intuitive to use a country's macroeconomic indicator to predict its own excess bond returns, Kose, Otrok, and Whiteman (2003, 2008) suggests that world economic business cycles are very likely to be driven by some global common factors. As such, the GMF may better capture time-varying risk aversion and changing investment opportunities. Hence, we also use the GMF to predict excess bond returns in international bond markets.

To investigate whether the predictive ability of real-time macro factors is above and beyond that contained in the influential and powerful Cochrane and Piazzesi (2005, CP hereafter) predictor, we also predict excess bond returns out-of-sample by estimating the following two predictive regressions

$$rx_{t+1}^{(n)} = \alpha + \beta CP_t + \varepsilon_{t+1}, \tag{19}$$

$$rx_{t+1}^{(n)} = \alpha + \beta_1 X_t + \beta_2 CP_t + \varepsilon_{t+1}, \tag{20}$$

where CP_t denotes the Cochrane-Piazzesi predictor. If the predictive ability of regression (20) is beyond the predictive power of regression (19), the predictive ability of X_t is not consumed by the CP predictor.

The CP predictor is constructed in the standard way. We regress average excess returns across maturities at each time t on the one-year yield and the four years forward rates

$\mathbf{f}_t \equiv [y_t^{(1)}\ f_t^{(2)}\ f_t^{(3)}\ f_t^{(4)}\ f_t^{(5)}]^T$:

$$\overline{rx}_{t+1} = \gamma_0 + \boldsymbol{\gamma}^T \mathbf{f}_t + \bar{\varepsilon}_{t+1}, \tag{21}$$

where the average excess log return across the maturity spectrum is defined as

$$\overline{rx}_{t+1} \equiv \frac{1}{4} \sum\nolimits_{n=2}^{5} rx_{t+1}^{(n)}. \tag{22}$$

Then the predictor is computed from

$$CP_{t+1} = \gamma_0 + \boldsymbol{\gamma}^T \mathbf{f}_t. \tag{23}$$

The predictor implies that the same function of forward rates predicts excess bond returns at all maturities.

To avoid look-ahead bias and the use of future data, we generate out-of-sample forecasts of excess bond returns using a recursive expanding estimation method. In the out-of-sample exercise, the GMF, LMF, and CP factors are recursively constructed, using only information upon time t. All predictive regression parameters are estimated just using information available up to the month of forecast formation. More specifically, we estimate and forecast recursively, using data from the first observation to the time that the forecast is made, beginning in 1992:01 and extending through 2014:12.

3.3 Forecast evaluation

A natural empirical benchmark for judging the predictive ability of leading economic indicators is the expectations hypothesis of interest rates. According to this hypothesis, excess bond returns are unpredictable, and the historical average is the optimal forecast of excess bond returns. Any predictability in bond risk premia is a violation of the expectations hypothesis of interest rates. In light of the fundamental role of the expectations hypothesis, we choose the expectations hypothesis as the most natural benchmark. Specifically, the historical average of excess bond returns is

$$\overline{rx}_{t+1}^{(n)} = \frac{1}{t} \sum\nolimits_{j=1}^{t} rx_j^{(n)}. \tag{24}$$

Indeed, when a predictor contains no useful information for predicting bond risk premia ($\beta = 0$ in regression (18)), the predictive regression becomes the historical average forecast.

A popular measure of out-of-sample predictive ability is the out-of-sample R^2 statistic, R^2_{OS}, proposed by Campbell and Thompson (2008) to compare the forecasting power of various regressions. Let $\widehat{rx}^{(n)}_{t+1}$ denote the forecast of excess bond returns generated by a predictive regression, the R^2_{OS} statistic is akin to the familiar in-sample R^2 statistic and is given by

$$R^2_{OS} = 1 - \frac{\sum_{j=1}^{T} (rx^{(n)}_j - \widehat{rx}^{(n)}_j)^2}{\sum_{j=1}^{T} (rx^{(n)}_j - \overline{rx}^{(n)}_j)^2}. \tag{25}$$

The R^2_{OS} statistic measures the reduction in mean square prediction errors (MSPE) for the predictive regression model relative to the expectations hypothesis. It is clear from the definition of the R^2_{OS} statistic that $R^2_{OS} > 0$ ($R^2_{OS} < 0$) implies that the $\widehat{rx}^{(n)}_{t+1}$ forecast statistically outperforms (underperforms) the historical average forecast according to the MSPE metric.

We further test whether the GMF has a significantly lower MSPE than the expectations hypothesis benchmark. Statistically, this is equivalent to testing the null hypothesis that $R^2_{OS} \leq 0$ against the alternative hypothesis that $R^2_{OS} > 0$. For this purpose, Clark and West (2007) develop the *MSPE-adjusted* statistic, which is an adjusted version of the Diebold and Mariano (1995) and West (1996) statistic. In contrast with the Diebold-Mariano test, the MSPE-adjusted test generates asymptotically valid inference when comparing forecasts from nested linear models.[3] Hence, the MSPE-adjusted test can be applied to compare the relative forecasting performance of two nested models. Since the historical average of excess bond returns is a restricted predictive regression (18) with $\beta = 0$, we use the MSPE-adjusted method to test the statistical significance of R^2_{OS} statistics. Specifically, the MSPE-adjusted statistic is conveniently calculated by first defining

$$f_{t+1} = (rx^{(n)}_{t+1} - \overline{rx}^{(n)}_{t+1})^2 - [(rx^{(n)}_{t+1} - \widehat{rx}^{(n)}_{t+1})^2 - (\overline{rx}^{(n)}_{t+1} - \widehat{rx}^{(n)}_{t+1})^2]. \tag{26}$$

[3] The Diebold and Mariano (1995) and West (1996) method generates a nonstandard distribution for comparing nested models.

By regressing $\{f_{t+1}\}_{t=1}^{T-1}$ on a constant and calculating the t-statistic corresponding to the constant, a p-value for a one-sided (upper-tail) test is obtained with the standard normal distribution. Clark and West (2007) demonstrate that the MSPE-adjusted statistic performs reasonably well in terms of power and size properties.

3.4 Economic value

Since statistical significance does not mechanically imply economic significance, it is important to assess the economic value of predictors. Following Campbell and Thompson (2008), Thornton and Valente (2012), Welch and Goyal (2008), and Rapach, Strauss, and Zhou (2010), we calculate realized utility gains for a mean-variance investor on a real-time basis. The method we employ explicitly accounts for the risk borne by an investor over the out-of-sample period. Specifically, we first calculate the average utility for a mean-variance investor with relative risk aversion parameter γ who allocates his or her portfolio monthly between a long-term bond and a one-year short-term Treasury bond using forecasts of excess bond returns based on the expectations hypothesis. This exercise requires the investor to forecast the variance of excess bond returns. In the spirit of Campbell and Thompson (2008), we assume that the investor estimates the variance using a ten-year rolling window of annual returns. A mean-variance investor who predicts excess bond returns using the historical average will decide at the end of period t to allocate the following share of his or her portfolio to the long-term bond in period $t+1$:

$$\bar{w}_t = \frac{1}{\gamma} \frac{\overline{rx}_{t+1}^{(n)}}{\hat{\sigma}_{t+1}^2}, \tag{27}$$

where $\hat{\sigma}_t^2$ is the ten-year rolling-window estimate of the variance of excess returns.[4] Over the out-of-sample period, the investor realizes an average utility level of

$$\bar{v} = \bar{\mu} - \frac{1}{2}\gamma\bar{\sigma}^2, \tag{28}$$

[4] $w_{0,t}$ is restricted to be positive and less than 150% at maximum so that extreme investments are prevented, as in Campbell and Thompson (2008), Goyal and Welch (2008), and Rapach, Strauss, and Zhou (2010).

where $\bar{\mu}$ and $\bar{\sigma}^2$ are the sample mean and variance, respectively, over the out-of-sample period for the return on the benchmark portfolio formed using forecasts of excess bond returns based on the historical average.

We then calculate the average utility of the trading strategy based on predictive regression (18). Similarly, the investor will choose a long-term bond share of

$$\hat{w}_t = \frac{1}{\gamma} \frac{\widehat{rx}_{t+1}^{(n)}}{\hat{\sigma}_{t+1}^2}, \tag{29}$$

and realizes an average utility level of

$$\hat{v} = \hat{\mu} - \frac{1}{2}\gamma\hat{\sigma}^2, \tag{30}$$

where $\hat{\mu}$ and $\hat{\sigma}^2$ are the sample mean and variance, respectively, over the out-of-sample period for the return on the portfolio formed using predictive regression (18). The utility gain of using predictive variables is the difference between Equation (30) and Equation (28):

$$\Delta = \hat{v} - \bar{v}. \tag{31}$$

The utility gain can be interpreted as the portfolio management fee that an investor is willing to pay to have access to the additional information available in a predictive regression model.

3.5 Forecast encompassing

Forecast encompassing (e.g., Fair and Shiller, 1990) provides a means for comparing the information content in different forecasts. Consider two forecasting models i and j providing two forecasts $\widehat{rx}_{i,t+1}$ and $\widehat{rx}_{j,t+1}$, the optimal forecast of excess bond returns is given by

$$\widehat{rx}_{t+1}^{*} = (1-\lambda)\widehat{rx}_{i,t+1} + \lambda\widehat{rx}_{j,t+1}, \tag{32}$$

where $0 \leq \lambda \leq 1$. The intuition of forecast encompassing is straightforward: $\lambda = 0$ implies that the model i forecast encompasses the model j forecast, as model j does not contain additional information beyond that contained in model i for predicting bond risk premia. In contrast, $\lambda > 0$ indicates that the model i forecast does not encompass the model j forecast since the model j forecast is useful for forming the optimal forecast.

Harvey, Leybourne, and Newbold (1998, HLN henceforth) develop a statistic to test the null hypothesis that the model i forecast encompasses the model j forecast against the (one-sided) alternative hypothesis that the model i forecast does not encompass the model j forecast. Define $d_{t+1} = (\hat{u}_{i,t+1} - \hat{u}_{j,t+1})\hat{u}_{i,t+1}$, where $\hat{u}_{i,t+1} = rx_{t+1} - \widehat{rx}_{i,t+1}$ and $\hat{u}_{j,t+1} = rx_{t+1} - \widehat{rx}_{j,t+1}$. Letting $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$, the modified version of the HLN statistic can be expressed as

$$MHLN = T^{1/2}[\hat{Q}(\bar{d})^{-1/2}]\bar{d}, \tag{33}$$

where $\hat{Q}(\bar{d}) = \frac{1}{T}\hat{V}(\bar{d})$ with $\hat{V}(\bar{d})$ being the sample variance of $\{d_t\}_{t=1}^{T}$. HLN recommend using the $MHLN$ statistic and the t_T distribution to assess statistical significance.

4 Empirical Results

This section reports the summary statistics for international bond yields and briefly discusses the data set of real-time macroeconomic factors. Then, we conduct the out-of-sample forecasting analysis and report the out-of-sample forecasting performance in the following sections.

4.1 Data

For our empirical analysis, we study excess bond returns in four bond markets: the United States, the United Kingdom (UK), Japan (JP), and Germany (GM). Several reasons account for our choice of markets. First, these are the largest bond markets in the world. In a quarter review of Bank of International Settlement, Gruić and Wooldridge (2012) argue that, as of the mid-2012, the outstanding volume of bonds denominated in the currencies of these four countries makes up more than 70% of the world market. Second, these markets are very liquid. As such, our study on the predictability of excess bond returns is less subject to the effect of illiquidity. Third, for these currencies, almost all foreign exchange risks can be hedged. Fourth, a panel of real-time macroeconomic variables are available for these markets.

The data set of international interest rates is made up of end-of-month observations of the one- to five-year zero-coupon Treasury bond yields. The data samples respectively range from 1982:01 to 2014:12. The US yield data are obtained from the Fama-Bliss discount bond file in the Center for Research in Securities Prices (CRSP). We collect the UK data from the Bank of England. The Japanese data are obtained from the Ministry of Finance Japan. The German observations are obtained from the Bundesbank, the central bank of Germany. All bond yields are denominated in local currency.[5]

[Insert Figure 1 about Here]

[Insert Table 1 about Here]

Figure 1 plots the Treasury bond yields for maturities of 1-, 2-, 3-, 4- and 5-year. It clearly suggests some stylized facts of interest rates: bond yields in each market increase as the maturity of bonds increases; bond yields appear to be volatile; bond yields are very persistent. Furthermore, we find that bond yields in these major bond markets show a tendency of comovement (see, also, Jotikasthira, Le, and Lundblad, 2015). To illustrate the point, Table 1 reports the correlation coefficients between the average of bond yields in each market over the period 1982:01-2014:12. It is evident that international bond yields are highly correlated. The evidence is clearly indicative that some global common factors may predict international excess bond returns.

[Insert Table 2 about Here]

Following Cochrane and Piazzesi (2005) and Thornton and Valente (2012), we calculate annual excess returns on long-term bonds using monthly data for bond yields with maturities

[5] This implicitly means that international investors hedge currency risk in portfolio management. To illustrate the point, let y_t, y_t^*, s_t respectively denote the one-period domestic log interest rate, foreign log interest rate, and log exchange rate. The log excess return denominated in domestic currency for a domestic investor who invests in the foreign bond market is $rx_{t+1}^* = s_{t+1} - s_t + Y_{t+1}^* - y_t$, where $Y_{t+1}^* = p_{t+1}^{(n-1)} - p_t^n$ is the gross return denominated in foreign currency for holding an n-period foreign bond for one-period. If investors hedge currency risk using currency futures, no-arbitrage pricing implies that $s_{t+1} - s_t = y_t - y_t^*$. Finally, we have $rx_{t+1}^* = p_{t+1}^{(n-1)} - p_t^n - y_t^*$, which is equivalent to equation (3).

ranging between one and five years. The summary statistics of the annual international excess bond returns are reported in Table 2. We find that annual excess bond returns of different maturities in each market are highly correlated. To look at the level of bond risk premia, we find that the mean of excess bond returns ranges between 0.46% and 3.02%. However, we want to emphasize that excess bond returns are very volatile, as indicated by the volatilities of excess bond returns. Though the mean of excess bond returns is often small, excess bond returns vary a lot over the sample period. All excess bond returns are found to be statistically significant. We also report the autocorrelation coefficients of order 1 and 12 for international excess bond returns. The results suggest that excess bond returns are highly serially correlated.

[Insert Table 3 about Here]

Macroeconomic data are often subject to large revisions after initial release. Several authors have recently stressed that the revision process complicates the ex post analysis of macro data. Indeed, macroeconometric analysis based on real-time data often yields substantively different conclusions from work ignoring revisions. In this paper, we investigate the predictability of excess bond returns by real-time macroeconomic variables. We select a sample of real-time macro factors to maximize the total number of time series and cross-sectional observations. Following this criterion, we obtain 7 real-time macroeconomic series starting in January 1982 for Japan, Germany, and UK. To keep balance in the construction of the GMF, we also construct 7 real-time unrevised series for US. The unrevised real-time economic series for US are collected from the Archival Federal Reserve Economic Database (ALFRED) at the Federal Reserve Bank of St. Louis.[6] The real-time macroeconomic variables for Japan, Germany, and UK are obtained from OECD database. These series include measures of industrial production, employment, personal income, price indices and the money stock. Table 3 provides a detailed description of the macro data set and our sources.

[6]We appreciate outstanding research efforts undertaken at the Federal Reserve Banks of St. Louis and Philadelphia, making such data publicly available and easy to use (see, also, Croushore, 2006; Croushore and Stark, 2001).

4.2 Out-of-sample forecasting results

This section examines the one-month-ahead out-of-sample predictability of excess bond returns in four industrialized countries–the United States, the United Kingdom, Japan, and Germany. Our analysis of bond risk premium predictability in international markets proceeds in three steps. First, we investigate whether the LMF, extracted from a panel of local real-time macroeconomic variables, is able to predict international bond risk premia. Second, we examine whether the GMF contains information for future excess bond returns. If so, third, we investigate whether the predictive ability of the GMF is subsumed by the CP factor.

[Insert Table 4 about Here]

Panel A of Table 4 reports the out-of-sample forecasting results of using the LMF to predict international bond risk premia. The results are mixing. On the one hand, we find that the LMF can predict excess bond returns in Germany with the R^2_{OS} statistics ranging between 10.4% and 22.0%. When assessed using the Clark and West (2007) MSPE-adjusted statistic, these R^2_{OS} statistics are consistently significant at the 1% level. On the other hand, in the UK and JP bond markets, the LMF consistently delivers the negative R^2_{OS} statistics ranging between -8.11% and -23.6%, which are statistically insignificant. The US bond market provides mixing results: While the LMF delivers significantly positive R^2_{OS} statistics when predicting the excess returns of the 2- and 3-year Treasury bonds, the R^2_{OS} statistics are significantly negative when forecasting the risk premia of the 4- and 5-year discount bonds.

Given the statistical evidence, an open question is whether the statistical significance leads to economic significance. To assess the economic value of out-of-sample bond risk premium forecasts, Panel A of Table 4 presents the utility gains from an asset allocation perspective by setting $\gamma = 2$. The results are qualitatively similar for other reasonable γ values. In line with the statistical results, we find that the LMF usually delivers positive utility gains in the GM bond market. Though the LMF delivers negative R^2_{OS} statistics in the UK bond market, it consistently generates positive utility gains for a mean-variance investor, suggesting that investors are better off when using information contained in the LMF to predict bond risk premia. In the US and JP bond markets, the economic value analysis presents mixing results, in line with the results from statistical analyses. Overall, the results from predicting bond risk premia using LMFs are mixing.

We turn next to the detailed results for out-of-sample predictions of excess bond returns using the GMF. Panel B of Table 4 reveals that the GMF typically outperforms the historical average in terms of R^2_{OS} statistic. In the markets other than Japan, the R^2_{OS} statistics range between 5.71% and 22.8%. The average R^2_{OS} statistics for US, UK, JP, and GM are respectively 13.1%, 14.1%, 1.1%, and 15.6%. These results contrast substantially to the evidence from the LMP regressions. We also use the Clark and West (2007) MSPE-adjusted statistics to assess the significance of the better out-of-sample forecasting performance of the GMF, the results suggest that the R^2_{OS} statistics are consistently significant at the 5% level.

A large set of real-time macroeconomic series for member countries are used in constructing the GMF. To be intuitively more straightforward, we also use the first principle component of international macroeconomic variables to predict excess bond returns. This type of analysis can sharpen our understanding on the importance of international economic linkages for predicting bond risk premia. Panel C presents the empirical results. It suggests that the first principle component of international macro factors generally predicts bond returns and delivers positive economic value. Though the R^2_{OS}s are negative in the Japanese bond market, the first principle component of international macroeconomic variables generally delivers positive economic value. To summarize, the forecasting analysis indicates that international economic linkages matter for expected bond returns.

[Insert Figure 2 about Here]

To provide a visual impression of the consistency of the GMF's predictive ability over time, Figure 2 presents time-series plots of the differences between the cumulative square prediction error (CSPE) for the historical average benchmark and the predictive model based on the GMF. When the curve in each panel of Figure 2 increases, the GMF predictive model outperforms the historical average, while the opposite holds when the curve moves down. The plots conveniently illustrate whether a predictive model beats competitors for any particular out-of-sample period by redrawing the horizontal zero line to correspond to the start of the out-of-sample period. The figure suggests that the GMF generally performs well in the US, UK, and GM bond markets. It is noteworthy that the GMF performs extremely well during the financial crisis of 2007-2008. These results provide evidence on the consistency of the out-of-sample predictive power of the GMF. In contrast, the forecasting performance of the GMF in the JP bond market appears unstable.[7]

Panel B of Table 4 also presents the utility gains of the GMF. In portfolio management, we set $\gamma = 2$. It is evident that the GMF can generate systematic economic value. The average utility gains are respectively 1.67%, 2.01%, 0.04%, and 1.85% in the US, UK, JP, and GM markets. These results are largely robust to the risk-averse parameter. If we set the values of the relative risk-aversion coefficient to be 1 or 5, the conclusions are unchanged. Overall, it is safe to say that the GMF is statistically and economically significant in the prediction of international excess bond returns.

Though the GMF generates large R^2_{OS} statistics, we find the economic value of the GMF is only comparable to that from the stock market (see, for example, Rapach, Strauss, and Zhou, 2010). Our results are consistent with those reported in Goh, Jiang, Tu, and Zhou (2013). The economic value assessment is interesting in understanding why bond risk premia are much more predictable than excess stock returns in terms of R^2_{OS} statistics. As emphasized by Goh, Jiang, Tu, and Zhou (2013), although the bond market is much more predictable than the stock market in terms of out-of-sample R^2_{OS} statistics, the economic value from predicting stock returns and bond returns are comparable, suggesting that across financial markets, the economic value of forecasting is likely to be the same due to probably across market arbitrage or intermarket efficiency.

[Insert Table 5 about Here]

Our results indicate that the GMF is usually a better predictor of international bond risk premia than LMFs. To provide insights on forecast encompassing, we conduct the

[7] Since late 1990s, interest rates in Japan have been close to the zero lower bound, this may account for the empirical findings for Japan.

encompassing test to compare the information content of the LMF forecasting model and the GMF forecasting model. Table 5 presents p-values for the MHLN statistic applied to the 1992:01-2014:12 out-of-sample window. More specifically, Panel A reports the results for testing the null hypothesis that the LMF forecasting model encompasses the GMF forecasting model. Our analysis reveals that in 15 out of 16 forecasts the LMF model does not encompass the GMF model at a 10% significance level. Panel B presents the results for testing the null hypothesis that the GMF model encompasses the LMF model. The results indicate that the GMF model encompasses the LMF model in the US, UK, and JP bond markets. Broadly speaking, these results are consistent with those reported in Table 4, suggesting the importance of international business cycles for predicting bond returns.

Ilmanen (1995) and Dahlquist and Hasseltoft (2013) find that some global common term-structure factors are better predictors of international excess bond returns than local instruments. In the stock market, Harvey (1991) finds that global factors outperform local factors in the forecasting exercise. Our results are largely consistent with those of Ilmanen (1995), Dahlquist and Hasseltoft (2013), and Harvey (1991). Our findings may reflect the integrated nature of international bond markets. Naturally, bonk risk premia are driven by some global factors rather than local factors in an integrated market.

Cochrane and Piazzesi (2005) find that the CP factor strongly predicts bond risk premia. To check whether the information content of the GMF is subsumed by the CP factor, we conduct a model comparison analysis. Specifically, we compare the out-of-sample forecasting performance of specification (20) that includes both the GMF and the CP factor to the benchmark model (19) that includes just the CP factor. This comparison allows us to assess the incremental predictive power of the global factor above and beyond the predictive ability contained in the CP factor.

[Insert Table 6 about Here]

Table 6 reports the results from out-of-sample forecast comparisons. Panel A presents the forecasting results of the CP-factor only model. Consistent with Ludvigson and Ng (2009), Dahlquist and Hasseltoft (2013), and Zhu (2015), we find that the CP factor does strongly predict bond risk premia, with the R^2_{OS} statistics ranging between 13.8% and 36.3%. Statistically, all R^2_{OS} statistics are significant at the 5% level. Panel B reports the out-of-sample forecasting results of the two-factor (the GMF and local CP factor) model. The results show that the two-factor model performs very well. The R^2_{OS} statistics are large, ranging between 16.3% and 48.3%. All R^2_{OS} statistics are statistically significant at the 1% level. Indeed, the two-factor model consistently outperforms the CP-factor only model in terms of R^2_{OS} statistic. To test the significance of the better performance of the two-factor model, we conduct the Clark-West (2007) test. The testing results, indicated in Panel B, suggest that the better forecasting performance of the two-factor model is consistently significant at the 5% level. In addition to statistical significance, we also investigate whether the observed predictability patterns are economically significant. Table 6 reports the economic gains of the two-factor model and the CP-factor only model. For all markets, our empirical analysis reveals that the two-factor model typically delivers higher utility gains than the CP-factor only model, suggesting the economic significance of the GMF.

Dahlquist and Hasseltoft (2013) and Zhu (2015) show that the global CP factor predicts excess bond returns better than local CP factors. Along this line of literature, we use the data from 1982:01-2014:12 to recursively construct the global CP factor and use it to predict bond returns out-of-sample. We find that the global CP factor strongly predicts international bond returns. To evaluate the possibility that the global CP factor subsumes the information content of the GMF, Panel C and D report the results of forecasting bond returns using respectively the global CP factor as well as the global CP and GMF factors. We find that the two-factor model consistently outperforms the global CP factor model. In particular, the better performance of the two-factor model is generally significant at the 5% level, suggesting that the GMF provides additional predictive power for future bond returns. Similarly, the economic value analysis confirms that the GMF plays an important role in bond return forecasts.

4.3 The GMF and risk-premium factor

Cieslak and Povala (2015) explore the time variation in bond risk premia. They propose a novel method to construct predictive factors. Specifically, they decompose Treasury yields into inflation expectations and maturity-specific interest-rate cycles, which is defined as the component orthogonal to expected inflation. The short-maturity cycle captures the dynamics of the real short rate at the business-cycle frequency. Cochrane and Piazzesi (2005) show that time-varying bond risk premia has a one-factor structure. In this spirit, Cieslak and Povala (2015) use these maturity-specific interest-rate cycles to construct a risk-premium factor, $\widehat{cf}_t$, which captures the time variation in bond risk premia. They show that the risk-premium factor predict bond risk premia and subsumes the common bond return predictor obtained as a linear combination of forward rates.

[Insert Table 7 about Here]

An important question is whether the risk-premium factor subsumes the information content of macroeconomic factors. To provide insights on this issue, we respectively use the risk-premium factor, the risk-premium and US LMF factors, and the risk-premium and GMF factors to predict US excess bond returns. Table 7 presents the forecasting results. The first point to note is that the risk-premium factor strongly predicts bond risk premia, confirming the results of Cieslak and Povala (2015). When the US LMF is included in the forecasting regression, predictive regressions generate even higher R^2_{OS} statistics, which are consistently significant at the 1% level. The economic value analysis confirms that the two-factor predictive model can better predict bond risk premia. More importantly, the third raw in Table 7 confirms that the GMF contains additional information for predicting future bond returns. It is statistically significant at the 1% significant level. The economic value analysis also suggest that the GMF delivers additional utility gains. Statistically, a test on the null hypothesis that the two-factor predictive model beats the risk-premium factor only model suggests that the GMF has predictive ability on excess bond returns, above and beyond that contained in the risk-premium factor.

5 Additional Robustness Checks

This section checks the robustness of the baseline out-of-sample forecasting results. In light of the out-of-sample predictability of international excess bond returns, a natural concern is "data-snooping bias". We address this concern from four perspectives: (1) we conduct the 3-month-ahead forecasting analysis; (2) we investigate the predictive power of the GMF in other international bond markets; (3) we test whether our results are robust in the in-sample forecasting exercise;

5.1 3-month-ahead forecasting results

Up to now, we consider the one-month-ahead forecasts. It leaves open to the question of the forecasting performance of the GMF at longer forecasting horizons. It is well established that long-horizon forecasting exercises may be more informative than their shorter-horizon counterparts (see, for example, Lo and MacKinlay, 1989). To shed light on the robustness of the forecasting results reported in Table 4, we conduct the 3-month-ahead forecasting analysis.

The full sample period for the 3-month-ahead forecasting exercise is 1982:01–2014:12. Statistical and economic performance measures are calculated for the out-of-sample period 1992:01-2014:12 assuming $\gamma = 2$. The out-of-sample forecasting procedure involves fully recursive parameter estimation using data only through time t for forecasting at time $t + 3$.

[Insert Table 8 Here]

Table 8 reports the 3-month-ahead forecasting results. In contrast to the 1-month-ahead results, Panel A shows that, at the 3-month horizon, the LMF extracted from local real-time macroeconomic variables generally delivers positive R^2_{OS} statistics. Indeed, the LMF can significantly predict bond risk premia for the U.S., the U.K., and Japan. Consistent with the results of the 1-month-ahead forecasting exercise, the GM LMF still strongly predict bond risk premia. In summary, it is safe to say that the country-specific LMFs may contain important information about future bond risk premia.

Panel B of Table 8 reports the 3-month-ahead forecasting results for the predictive model based on the GMF. We find that the GMF consistently delivers statistically significant R^2_{OS} statistics. Indeed, 15 out of 16 R^2_{OS} statistics are positive, suggesting that the GMF predicts international bond risk premia. Importantly, we find that the GMF's forecasting performance is better than the LMF's performance in all markets except the GM bond market, In addition, our economic value analysis reveals that the GMF delivers systematic economic value. Indeed, all utility gains are positive, though some gains are economically small. Overall, these results confirm the importance of international economic linkages for understanding fluctuations in bond risk premia.

5.2 Predicting bond risk premia in other markets

So far, we find that the GMF predicts bond risk premia in major bond markets. An interesting question is whether the GMF can predict bond risk premia in other bond markets. Obtaining evidence on the forecasting power of the GMF, a measure of global economic conditions, in other bond markets is important because it can sharpen our understanding on the global common driving force of bond return movements. In this section, we conduct the out-of-sample forecasting analysis using government bond yields for Australia, Canada, New Zealand, and Switzerland.[8] We use maturities of one to five years for the four markets. Yields for Switzerland are derived from forward rates. The data start in January 1988 and end in December 2014. Yields for Australia and Canada are obtained from Reserve Bank of Australia and Bank of Canada. The sample period is respectively 1992:07-2014:12 and 1986:01-2014:12. Yields for New Zealand are obtained from Datastream. The data set starts in June 1987 and ends in December 2014.

We employ a recursive forecasting scheme. Specifically, forecasts are generated using parameters that are estimated using information available only at the time the forecast is made. The out-of-sample period is 2000:01-2014:12 for the four markets.

[Insert Table 9 about Here]

Table 9 evaluates the out-of-sample performance of the GMF in predicting international bond risk premia, using out-of-sample R^2_{OS} statistic and utility gain. Panel B reports the out-of-sample forecasting results using the GMF as the predictive variable. The R^2_{OS} statistics

[8] The yield curves in Euro-zone countries are highly correlated with those of Germany, though they diverged for a short period during the 2007-2008 financial crisis.

reveal that the GMF significantly predicts international excess bond returns, as 15 out of the 16 excess return forecasts produce a positive and statistically significant R^2_{OS} statistic.

In an attempt to provide insights on the additional predictive ability of the GMF above and beyond the CP factor, Panel A reports the out-of-sample forecasting results using the CP factor as the predictor. Panel C reports the forecasting results using both the CP factor and the GMF as predictive variables. By comparing the results reported in Panel A and C, it is evident that the GMF delivers additional predictive power for international bond risk premia, as 13 out of the 16 excess return forecasts generate a greater R^2_{OS} statistic. Furthermore, the two-factor model usually delivers higher utility gains than the CP-factor only model, suggesting that the GMF delivers additional economic value.

5.3 In-sample forecasting exercise

While a number of studies (e.g., Welch and Goyal, 2008; Thornton and Valente, 2012) emphasize the importance of out-of-sample forecasting performance, some weight should be placed on in-sample statistics in judging the predictability of excess bond return (e.g., Inoue and Kilian, 2004), we now test the in-sample forecasting performance of the LMF and GMF using the full sample starting in 1982:01 and continuing to the end of 2014.

[Insert Table 10 about Here]

The strategy performance which results from the in-sample forecasting exercise is tabulated in Table 10. Panel A shows how well the LMF can predict future bond risk premia. Contrast with the out-of-sample forecasting performance, we find that the LMF forecasts excess bond returns of all maturities for all countries in our sample. With only one exception, the LMF generates highly significant positive R-square. We further assess the economic value of the forecasting ability of empirical models based on the LMF in a dynamic asset allocation strategy. The results show that the information content of the LMF generate systematic economic value to investors.

Panel B reports the in-sample forecasting results of the predictive model based on the GMF. A pattern emerging from Panel B is that the GMF consistently delivers positive

R^2s, which are generally greater than ones from the predictive regressions based on LMFs. Another interesting pattern emerging from the Table is that the R^2s for all markets decrease as the maturity of Treasury bonds get longer. In addition, we assess the economic value of the predictive power of the GMF by investigating the utility gains accrued to investors who exploit the predictability of bond excess returns relative to a no-predictability alternative associated with the validity of the expectations hypothesis. The economic value analysis indicates that the GMF delivers systematic utility gains, which are typically higher than those generated by the LMF.

To shed light on the robustness of the predictive power of the GMF, we extract the first principle component from international real-time macroeconomic variables and use it to forecast bond risk premia. The results are tabulated in Panel C of Table 10. The R^2s of the forecasting regressions based on the first principle component are typically higher than those delivered by the predictive regressions based on the GMF and those generated by the forecasting models based on LMFs. We find that the predictive models based on the first principle component are able to add significant economic value to investors relative to the no-predictability benchmark. These results are complementary to those from the GMF regressions, suggesting that global macro risks play a critical role in understanding fluctuations in international bond risk premia.

6 Economic Links and the Role of US

6.1 Bond return forecasts and the business cycle

Economic theories suggest that rational, utility-maximizing investors must be compensated for bearing macroeconomic risks. In economic recessions, investors are reluctant to take on risk. Heightened risk aversion during economic downturns thus pushes up the risk premium. In light of this, we examine fluctuations in bon forecasts over the business cycle.

[Insert Figure 3 about Here]

Figure 3 shows the 5-year bond return forecasts and the year-over-year industrial production growth, along with shaded bars indicating business-cycle recessions.[9] Two general aspects of all figures are noteworthy. First, bond risk premia predicted by the GMF have a clear countercyclical component, consistent with economic theories suggesting that investors require a higher risk premium during economic recessions. In general, bond risk premium forecast takes its highest values over the out-of-sample period during recessions. This pattern is particularly clear for the United States. Second, bond risk premia predicted by the historical average appears to be too smooth. It is evident that they are acyclical. From an economic perspective, bond risk premia implied by the historical average fail to capture the business-cycle fluctuations and incorporate meaningful macroeconomic information. To summarize, the figure suggests that the GMF is an economically meaningful predictor of international bond risk premia.

6.2 The role of the United States

For stock returns, Rapach, Strauss, and Zhou (2013) identify a leading role for the United States. Specifically, they show that lagged U.S. returns predict stock returns in numerous non-U.S. industrialized countries substantially better than the countries' own economic variables such as interest rates and dividend yields. In contrast, lagged returns of non-U.S. countries have limited predictive ability for U.S. stock returns. These findings raise an interesting question: does the US bond market play a leading role in international markets? If yes, does the information content of US risk premia subsume the information content of the GMF.

[Insert Table 11 about Here]

To investigate the role of the United States, we conduct the out-of-sample forecasting analysis by using lagged US bond risk premia to predict international bond risk premia. The data samples respectively range from 1982:01–2014:12. Panel A of Table 11 reports

[9] We use NBER-dated business recessions for the United States. For all other three markets, the business cycle is dated by the Economic Cycle Research Institute (ECRI).

the forecasting results for the out-of-sample period from 1992:01–2014:12. The R^2_{OS}s of the forecasting models based on lagged US bond returns for Japan are consistently negative. Though the R^2_{OS} statistics are positive in predicting GM bond risk premia, the economic value of the predictive regression is consistently negative. The predictive regressions for the U.K. generate some positive and some negative R^2_{OS} statistics, which are typically small in magnitude. Taken together, these results seem to indicate that the US bond market does not dominate international bond markets.

While the forecasting analysis using lagged US bond returns hints whether the US bond market plays a leading role in international markets, a more interesting and fundamental question is whether the US economy in general matters for international bonds. To provide insights on this issue, Panel B of Table 11 reports the results for predicting international bond risk premia using the US LMF. We find that the R^2_{OS} statistics are generally negative. Similarly, the economic value of the US LMF is generally negative. On the other hand, our empirical analysis shows that individual foreign LMF is unlikely to robustly predict US bond returns. Overall, our empirical analysis suggests that neither the United States nor other countries play a leading role in international bond markets.

7 Other Asset Classes

As an aggregate measure of economic conditions, the GMF should also predict asset returns in other financial markets, as suggested by economic theories (Merton, 1973). In this section, we investigate the information content of the GMF for future stock returns and carry trade returns. In particular, we focus on whether the GMF contains information above and beyond that contained in local LMFs.

7.1 The stock market

On the theoretical side, any variable that affects the future investment opportunity set or consumption could be a priced factor in general equilibrium. Naturally, investors require higher risk premia to take on risk in economic recessions. As a result, the market's expectation of future economic conditions is an important driver of stock price movements.

Empirically, a large literature has examined the predictability of stock returns using macroeconomic indicators. In particular, some prime business cycle indicators have been identified as the predictor of stock returns such as aggregate output (e.g., Cooper and Priestley, 2013; MØller and Rangvid, 2015), the output gap (e.g., Cooper and Priestley, 2008), and production growth rates (e.g., Fama, 1990; Schwert, 1990).

In recent years, international stock markets have become more integrated. In particular, developed markets are believed to be highly integrated. The integrated stock market suggests that the GMF, a global leading economic indicator, should contain information about future stock returns, above and beyond the information contained in local LMFs. To shed light on this hypothesis, we conduct the out-of-sampling forecasting exercise to investigate the relative predictive power of the GMF and local LMFs.

Toward this end, we estimate predictive regressions for four major stock markets: the United States, the United Kingdom, Japan, and Germany. Our monthly sample spans 1982:01 to 2014:12. We use monthly S&P 500 index returns from Center for Research in Security Prices for US. The monthly country index returns for other markets are from Thomson Financial Datastream series in local currencies. As a check, we compare these total market returns to local value-weighted returns from Kenneth French's Website when available. The respective total return series are at least 95% correlated between the two sources, but we employ the Datastream return series because it has better overall coverage. The out-of-sample period covers 1992:01–2014:12.

[Insert Table 12 about Here]

Table 12 reports the results of predicting monthly stock returns using local LMFs and the GMF. We begin by discussing return forecasts with local LMFs being the only predictor. We find that in 3 out of 4 markets, the LMF cannot predict stock returns. The economic value of the predictive regressions based on the LMF is negative or close to zero. Though the R^2_{OS} statistic for the United States is positive, it is only marginally significant. Next, we discuss monthly return forecasts with the GMF being the predictor. The out-of-sample forecasting analysis indicates that the GMF consistently outperforms the LMF in terms of R^2_{OS} statistic and economic value. Except Japan, the GMF beats the historical average benchmark for other three markets. To summarize, the out-of-sample forecasting analysis seems to suggest that the GMF contains additional information for predicting future stock returns, above and beyond that contained in LMFs.

7.2 Currency markets

Currencies are actively traded in the spot and forward market. In particular, the "carry trade" strategy, which borrows in currencies with low interest rates and invests in currencies with high interest rates, have been shown to deliver high Sharpe ratios. Since carry trade strategies are potentially risky investment, a risk-based explanation of carry trade returns has attracted a lot of attention. To date, the literature has identified a few risk factors to enhance our understanding on carry trade returns such as aggregate consumption risk (Lustig and Verdelhan, 2007), the slope factor in exchange rates (Lustig, Roussanov, and Verdelhan, 2011), global foreign exchange volatility (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012), and downside risk (e.g., Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2011; Lettau, Maggiori, and Weber, 2014).

Though there are various risk factors, it appears to be well-accepted that the carry trade premium is partially determined by the global risk in financial markets. Since the GMF is a global economic indicator, it is naturally to hypothesize that the GMF contains information about carry trade returns. In this section, we focus on carry trade investments. Specifically, we examine the time series predictability of carry trade returns (e.g., Bakshi and Panayotov, 2013). Our questions include: Does the GMF predict carry trade returns? If so, is such predictability statistically and economically significant? To provide insights on these questions, we conduct the out-of-sampling forecasting exercise to investigate the predictive power of the month-over-month log change in the global leading economic indicator.

To calculate currency excess returns, we use s to denote the log of the nominal exchange rate in units of foreign currency per U.S. dollar, and f for the log of the forward exchange rate, also in units of foreign currency per U.S. dollar. The log excess return rx on buying a foreign currency in the forward market and selling it in the spot market after one month is

$$rx_{t+1} = f_t - s_{t+1}.$$

According to no-arbitrage conditions, forward rates satisfy the covered interest rate parity condition: $f_t - s_t \approx y_t^* - y_t$, where y_t^* and y_t denote foreign and domestic interest rates. Using this equality, the currency excess return can be rewritten as

$$rx_{t+1} = y_t^* - y_t - \Delta s_{t+1},$$

where $\Delta s_{t+1} = s_{t+1} - s_t$. In the spirit of Lustig, Roussanov, and Verdelhan (2011), we use the data on bid-ask spreads quotes for spot and forward contracts to compute the investor's actual realized return net of transaction costs.

Spot and forward exchange rates span 1983:11-2014:12. We focus on the developed countries, so the main dataset contains 15 developed countries: Australia, Belgium, Canada, Denmark, euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. In the spirit of Lustig and Verdelhan (2007) and Lustig, Roussanov, and Verdelhan (2011), at the end of each month, we allocate all currencies in the sample to five portfolios on the basis of their forward discount $f-s$ observed at the end of period t. Portfolios are rebalanced on a monthly basis. These five portfolios are then ranked from low to high interest rates: portfolio 1 contains the currencies with the lowest interest rate, and portfolio 5 contains the currencies with the highest interest rates. The carry trade returns are respectively calculated as the return of portfolio j ($j = 2, 3, 4, or$ 5) minus the return of portfolio 1.[10] To obtain intuition on how profitable is carry trade, our calculation indicates that the annualized average returns for portfolio 2, 3, 4, and 5 are respectively 1.20%, 3.38%, 3.22%, and 5.38%.

[Insert Table 13 about Here]

[10]The portfolio returns are available at https://sites.google.com/site/lustighanno/. We thank Hanno Lustig, Nikolai Roussanov, and Adrien Verdelhan for making the dataset available and for updating the dataset.

We estimate predictive regressions (18) for the four series of carry trade returns. We use the first 10-year window as the in-sample period. We recursively estimate and forecast carry trade returns over the out-of-sample period 1993:12-2014:12. The forecasting variable is the GMF.[11] The empirical benchmark is the historical average. Table 13 presents the out-of-sample forecasting results. We find that all R^2_{OS} statistics are positive. As indicated by the MSPE-adjusted test, these R^2_{OS} statistics are statistically significant at the 10% level. The economic analysis suggests that the GMF can generate systematic positive economic value for predicting carry trade returns. These results indicate that GMF contains important information regarding future carry trade returns.

8 Conclusions

This paper investigates the question as to what macroeconomic risks that drive the bond risk premia across countries. Complimenting to existing theories on the role of macroeconomic risks on explaining bond time-varying risk premia, we provide the first strong evidence on bond predictability by real-time macroeconomic variables. In particular, we construct a global macroeconomic factor (GMF), a measure of the aggregate state of the world economy, and shows that it has important predictive power for international bond returns. In contrast, country-specific real-time economic indicators and macro factors provide only mixed forecasting results. Our results suggest that international bond markets are integrated, and the same global factor is largely responsible for the dynamics of international bond risk premia. We also contribute to the literature by showing that the GMF can predict international stock returns and carry trade returns, thus providing an economic link of various risk premia across asset classes.

Since statistical significance does not necessarily imply economic significance, we examine also the economic significance of the GMF. In particular, we evaluate the utility gains accrued to investors who use the predictive model based on the GMF to forecast bond risk premia versus ignoring the predictability completely. Our analysis shows that the GMF has

[11] As emphasized by Lustig, Roussanov, and Verdelhan (2011), the total number of currencies in the currency portfolios varies over time. So, we do not forecast the carry trade returns using LMFs.

economically and statistically meaningful forecasting power on the international bond risk premia.

We have two remarks on our findings. First, we find that a global aggregate measure of the state of the economy can predict bond risk premia across countries better than country macroeconomic variables. This is important because economic theories generally imply that risk-averse economic agents should be compensated for bearing macroeconomic risks, and our study simply says that it is the global macroeconomic risks. The predictive power of the GMF is supportive for developing new bond pricing models that incorporate global economic factors in an integrated model of the world markets. Second, the predictive power of the GMF is above and beyond the information contained in the Cochrane-Piazzesi (2005) forward rate predictor and the risk-premium factor (Cieslak and Povala, 2015). Hence, our analysis contributes to the literature on bond predictability by finding the GMF as a new predictor whose significant economic value indicates practical applicability for managing bond portfolios. As part of future research, it will be of interest to investigate whether the GMF can predict returns on large mutual and hedge fund returns in assessing their global economic risk exposures.

References

[1] Bakshi, G. and Panayotov, G., 2013. Predictability of currency carry trades and asset pricing implications. Journal of Financial Economics 110, 139–163.

[2] Balvers, R.J., Cosimano, T.F., and Mcdonald, B., 1990. Predicting stock returns in an efficient market. Journal of Finance 45, 1109–1128.

[3] Bauer, M.D., and Hamilton, J.D., 2016. Robust bond risk premia. Working Paper.

[4] Bauer, M.D., and Rudebusch, G.D., 2016. Resolving the spanning puzzle in macro-finance term structure models. Working Paper.

[5] Belo, F., 2010. Production-base measures of risk for asset pricing. Journal of Monetary Economics 57, 146–163.

[6] Buraschi, A., and Jiltsov, A., 2007. Habit formation and macroeconomic models of the term structure of interest rates. Journal of Finance 62, 3009–3063.

[7] Burnside, C., Eichenbaum, M., Kleshchelski, I., and Rebelo, S., 2011. Do peso problems explain the returns to the carry trade? Review of Financial Studies 24, 853–891.

[8] Campbell, J.Y., and Shiller, R., 1991. Yield spreads and interest rates: A bird's eye view. Review of Economic Studies 58, 495–514.

[9] Campbell, J.Y., and Thompson, S.B., 2008. Predicting excess stock returns out of sample: Can anything beat the historical average. Review of Financial Studies 21, 1509–1531.

[10] Cieslak, A., and Povala, P., 2015. Expected returns in treasury bonds. Review of Financial Studies 28, 2859–2901.

[11] Clark, T.E., and West, K.D., 2007. Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics 138, 85–110.

[12] Cochrane, J.H. 1991. Production-based asset pricing and the link between stock returns and economic fluctuations. Journal of Finance 461, 209–237.

[13] Cochrane, J.H., and Piazzesi. M., 2005. Bond risk premia. American Economic Review 95, 138–160.

[14] Cochrane, J.H. and Piazzesi, M., 2008. Decomposing the yield curve. Mimeo, University of Chicago and University of Stanford.

[15] Cooper, I., and Priestley, R., 2008. Time-varying risk premiums and the output gap. Review of Financial Studies 22, 2801–2833.

[16] Cooper, I., and Priestley, R., 2013. The world business cycle and expected returns. Review of Finance 17, 1029–1064.

[17] Croushore, D., 2006. Forecasting with real-time macroeconomic data. in Handbook of Economic Forecasting, ed. by G. Elliott, C. Granger, and A. Timmermann, vol. 1, pp.961–982. Elsevier.

[18] Croushore, D., and Stark, T,. 2001. A real-time data set for macroeconomists. Journal of Econometrics, 105, 111–130.

[19] Dahlquist M., and Hasseltoft, H., 2013. International bond risk premia. Journal of International Economics 90, 19–32.

[20] Diebold, F.X., and Mariano, R.S., 1995. Comparing predictive accuracy. Journal of Business and Economic Statistics 13, 253–263.

[21] Duffee, G., 2011. Information in (and not in) the term structure. Review of Financial Studies 24, 2895–2934.

[22] Eriksen, J.N., 2016. Expected business conditions and bond risk premia. Journal of Financial and Quantitative Analysis, forthcoming.

[23] Fair, R.C., and Shiller, R.J., 1990. Comparing information in forecasts from econometric models. American Economic Review 80, 375–89.

[24] Fama, E.F., 1990. Stock returns, expected returns, and real activity. Journal of Finance 45, 1089–1108.

[25] Goh, J., Jiang, F., Tu, J., and Zhou, G., 2013. Forecasting government bond risk premia using technical indicators. Working Paper, University of Washington at St. Louis.

[26] Ghysels, E., Horan, C., and Moench, E., 2014. Forecasting through the Rear-view Mirror: Data Revisions and Bond Return Predictability. Working Paper.

[27] Harvey, C.R. 1991. The world price of covariance risk. Journal of Finance 46, 111–157.

[28] Harvey, D.I., Leybourne, S.J., and Newbold, P., 1998. Tests for forecast encompassing. Journal of Business and Economic Statistics 16, 254–59.

[29] Ilmanen, A., 1995. Time-varying expected returns in international bond markets. Journal of Finance 50, 481–506.

[30] Inoue, A., and Kilian, L., 2004. In-sample or out-of-sample tests of predictability: Which one should we use? Econometric Reviews 23, 371–402.

[31] Jotikasthira, C., Le, A., and Lundblad, C., 2015. Why do term structures in different currencies co-move? Journal of Financial Economic 115, 58–83.

[32] Joslin, S., Priebsch M., and Singleton, K.J., 2014. Risk premiums in dynamic term structure models with unspanned macro risks. Journal of Finance 69, 1197–1233.

[33] Jermann, U.J., 2013. A production-based model for the term structure. Journal of Financial Economics 109, 293-306.

[34] Kelly, B.T., and Pruitt, S., 2012. The three-pass regression filter: A new approach to forecasting with many predictors. Working paper, Chicago Booth.

[35] Kelly, B.T., and Pruitt, S., 2013. Market expectations in the cross-section of present values. Journal of Finance 68, 1721–1756.

[36] Kose, M.A., Otrok, C., and Whiteman, C.H., 2003. International business cycles: world, region, and country-specific factors. American Economic Review 93, 1216–1239.

[37] Kose, M.A., Otrok, C., and Whiteman, C.H., 2008. Understanding the evolution of world business cycles. Journal of International Economics 75, 110–130.

[38] Lettau, M., Maggiori, M., and Weber, M., 2014. Conditional risk premia in currency markets and other asset calsses. Journal of Financial Economics 114, 197–225.

[39] Lo, A., andMacKinlay, C., 1989. The size and power of the variance ratio test in finite samples: A monte carlo investigation. Journal of Econometrics 40, 203–238.

[40] Lucas, R.E. 1993. Making a miracle. Econometrica 22, 3–42.

[41] Ludvigson, S.C., and Ng, S., 2009. Macro factors in bond risk premia. Review of Financial Studies 22, 5027–5068.

[42] Lustig, H., Roussanov, N., and Verdelhan, A., 2011. Common risk factors in currency markets. Review of Financial Studies 24, 3731–3777.

[43] Lustig, H., and Verdelhan, A., 2007. The cross section of foreign currency risk premia and consumption growth risk. American Economic Review 97, 89–117.

[44] Menkhoff, L., Sarno, L., Schmeling, M., and Schrimpf, M., 2012. Carry trades and global foreign exchange volatility. Journal of Finance 67, 681–718.

[45] Merton, R.C., 1973. An intertemporal asset pricing model. Econometrica 41, 867– 887.

[46] MØller, S.V., and Rangvid, J., 2015. End-of-year economic growth and time-varying expected returns. Journal of Financial Economics 115, 136–154.

[47] Piazzesi, M., and Schneider, M., 2006. Equilibrium yield curves. NBER Macroeconomic Annual 2006, 389–442.

[48] Rapach, D.E., Strauss, J.K., and Zhou, G., 2010. Out-of-sample equity premium prediction: combination forecasts and links to the real economy. Review of Financial Studies 23, 821–862.

[49] Rapach, D.E., Strauss, J.K., and Zhou, G., 2013. International stock return predictability: What is the role of the united states? Journal of Finance 68, 1633–1662.

[50] Rizova, S. 2010. Predictable trade flows and returns of trade-linked countries. Working Paper, University of Chicago.

[51] Sarno, L., Schneider, P., and Wagner, C., 2016. The economic value of predicting bond risk premia. Journal of Empirical Finance 37, 247–267.

[52] Schwert, G.W., 1990. Stock returns and real activity: A century of evidence. Journal of Finance 45, 1237–1257.

[53] Stambaugh, R.F., 1988. The information in forward rates: Implications for models of the term structure. Journal of Financial Economics 21, 41–70.

[54] Thornton, D.L., and Valente, G., 2012. Out-of-sample predictions of bond excess returns and forward rates: An asset allocation perspective. Review of Financial Studies 25, 3141–3168.

[55] Wachter, J., 2006. A consumption-based model of the term structure of interest rates. Journal of Financial Economics 79, 365–399.

[56] Welch, I., and Goyal, A., 2008. A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies 21, 1455–1508.

[57] West, K.D., 1996. Asymptotic inference about predictive ability. Econometrica 61, 1067–84.

[58] Young, A. 1991. Learning by doing and the dynamic effects of international trade. Quarterly Journal of Economics 106, 369–405.

[59] Wold, H., 1975, Estimation of principal components and related models by iterative least squares, in P.R. Krishnaiaah, ed.: Multivariate Analysis (Academic Press, New York).

[60] Wright, J., 2011. Term premia and inflation uncertainty: Empirical evidence from an international panel dataset. Americian Economic Review 101, 1514–1534.

[61] Zhu, X., 2015. Out-of-sample bond risk premium predictions: A global common factor. Journal of International Money and Finance 51, 155-173.

Table 1: Correlation Coefficients between Average Bond Yields

	$\overline{y}_{t+1}^{US}$	$\overline{y}_{t+1}^{UK}$	$\overline{y}_{t+1}^{JP}$	$\overline{y}_{t+1}^{GM}$
$\overline{y}_{t+1}^{US}$	1.00	-	-	-
$\overline{y}_{t+1}^{UK}$	0.931	1.00	-	-
$\overline{y}_{t+1}^{JP}$	0.848	0.888	1.00	-
$\overline{y}_{t+1}^{GM}$	0.844	0.924	0.854	1.00

The table reports the pairwise correlation coefficients between the average yields on the 1-, 2-, 3-, 4-, and 5-year government bonds for US, UK, Japan, and Germany. The sample period is 1982:01 to 2014:12. The average bond yield in each market is calculated as $\overline{y}_{t+1} \equiv \frac{1}{5}\sum_{n=1}^{5} y_{t+1}^{(n)}$.

Table 2: Summary Statistics of International Excess Bond Returns

Maturity	Central Moments		Autocorrelations	
	Mean	Std Dev	Lag 1	Lag 12
		US		
$rx_t^{(2)}$	1.020***	1.538	0.936***	0.063
$rx_t^{(3)}$	1.854***	2.893	0.934***	-0.048
$rx_t^{(4)}$	2.590***	4.082	0.922***	-0.100
$rx_t^{(5)}$	3.022***	5.076	0.912***	-0.162
		UK		
$rx_t^{(2)}$	0.563***	1.549	0.932***	0.103
$rx_t^{(3)}$	1.175***	2.871	0.924***	-0.013
$rx_t^{(4)}$	1.729***	4.062	0.916***	-0.074
$rx_t^{(5)}$	2.234***	5.114	0.910***	-0.097
		Japan		
$rx_t^{(2)}$	0.463***	0.933	0.941***	0.285**
$rx_t^{(3)}$	1.011***	1.820	0.935***	0.247*
$rx_t^{(4)}$	1.583***	2.680	0.930***	0.215
$rx_t^{(5)}$	2.122***	3.451	0.930***	0.188
		Germany		
$rx_t^{(2)}$	0.742***	1.247	0.943***	0.189**
$rx_t^{(3)}$	1.484***	2.354	0.941***	0.111
$rx_t^{(4)}$	2.113***	3.286	0.939***	0.059
$rx_t^{(5)}$	2.648***	4.104	0.937***	0.022

The table summarizes the descriptive statistics for annual international excess bond returns. The data samples range from 1982:01 to 2014:12. The excess bond returns are expressed in percentage points per annum. *,**, and *** denote statistical significance at the 10%, 5%, or 1% confidence level, and statistical significance is evaluated using the Newey-West (1987) autocorrelation and heteroscedasticity-consistent standard errors.

Table 3: Real-time Macroeconomic Variables

Description	Data Source	Tran
US		
Civilian Employment	Archival FRED	$\Delta \ln$
CPI for all urban consume:all items	Archival FRED	$\Delta \ln$
Disposable personal income	Archival FRED	$\Delta \ln$
Industrial production index	Archival FRED	$\Delta \ln$
M2 money stock	Archival FRED	$\Delta \ln$
Personal consumption expenditures	Archival FRED	$\Delta \ln$
UK		
Industrial production index	OECD	$\Delta \ln$
Consumer price index	OECD	$\Delta \ln$
International trade in goods-exports	OECD	$\Delta \ln$
International trade in goods-imports	OECD	$\Delta \ln$
Composite leading indicators	OECD	$\Delta \ln$
Retail trade volume	OECD	$\Delta \ln$
Hourly earnings in manufacturing	OECD	$\Delta \ln$
Japan		
Industrial production index	OECD	$\Delta \ln$
Consumer price index	OECD	$\Delta \ln$
International trade in goods-exports	OECD	$\Delta \ln$
International trade in goods-imports	OECD	$\Delta \ln$
Composite leading indicators	OECD	$\Delta \ln$
Retail trade volume	OECD	$\Delta \ln$
Hourly earnings in manufacturing	OECD	$\Delta \ln$
Germany		
Industrial production index	OECD	$\Delta \ln$
Consumer price index	OECD	$\Delta \ln$
International trade in goods-exports	OECD	$\Delta \ln$
International trade in goods-imports	OECD	$\Delta \ln$
Composite leading indicators	OECD	$\Delta \ln$
Retail trade volume	OECD	$\Delta \ln$

The table provides a breif description of real-time macroeconomic series for US, UK, Japan, and Germany and their data sources. $\Delta \ln$ denotes the first difference of the logarithm. The data span the period from 1982:01 to 2014:12.

Table 4: Excess Bond Return Predictions: LMF and GMF

	US		UK		Japan		Germany	
	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$
Panel A: The LMF								
$rx_t^{(2)}$	3.3***	0.49	-6.75	0.55	-23.6	0.47	22.0***	2.15
$rx_t^{(3)}$	0.7***	0.40	-8.11	0.87	-20.8	-0.37	16.9***	1.71
$rx_t^{(4)}$	-3.2***	-0.43	-9.13	1.24	-17.7	-0.80	13.2***	1.53
$rx_t^{(5)}$	-4.4***	-0.41	-8.74	1.63	-16.2	-1.27	10.4***	1.35
Panel B: The GMF								
$rx_t^{(2)}$	18.7***	2.78	21.9***	2.82	-11.9***	0.35	22.8***	2.36
$rx_t^{(3)}$	14.7***	1.73	16.5***	1.88	-6.55***	-0.16	15.8***	1.98
$rx_t^{(4)}$	11.9***	1.22	12.3***	1.44	9.25*	0.21	12.7***	1.72
$rx_t^{(5)}$	7.12***	0.95	5.71***	1.90	13.6**	-0.24	11.2***	1.35
Panel C: The first PC of international real-time macro factors								
$rx_t^{(2)}$	17.9***	1.18	9.37***	2.07	-19.8***	0.73	11.5***	1.85
$rx_t^{(3)}$	10.7***	0.99	5.65***	1.79	-18.3***	0.49	7.82***	1.80
$rx_t^{(4)}$	5.65***	0.72	1.83***	1.39	-14.9***	0.19	6.35***	1.89
$rx_t^{(5)}$	3.76***	0.51	-0.90***	1.51	-11.7***	-0.67	11.5***	1.95

The table reports the out-of-sample R^2 statistics for log excess bond returns on the n-year long-term Treasury bond over the 1992:01-2014:12 forecast evaluation period. Utility gain (Δ) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of two would be willing to pay to have access to the forecasting model. Panels A, B and C respectively present the results for the forecasting model with the LMF, GMF, and the first principle components of global macro factors as predictors. For computing utility gain, the weight on long-term bonds in the investor's portfolio is restricted to lie between zero and 1.5 (inclusive). Statistical significance for the out-of-sample R^2 is based on the p-value for the Clark and West (2007) out-of-sample MSPE-adjusted statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Forecast Encompassing Test Results: LMF and GMF

	US	UK	Japan	Germany
Panel A. LMF encompass GMF				
$rx_t^{(2)}$	0.00	0.00	0.01	0.00
$rx_t^{(3)}$	0.00	0.00	0.00	0.07
$rx_t^{(4)}$	0.00	0.00	0.00	0.11
$rx_t^{(5)}$	0.00	0.00	0.00	0.03
Panel B. GMF encompasses LMF				
$rx_t^{(2)}$	0.15	0.11	0.57	0.10
$rx_t^{(3)}$	0.20	0.43	0.72	0.04
$rx_t^{(4)}$	0.16	0.76	0.68	0.03
$rx_t^{(5)}$	0.28	0.73	0.21	0.08

The table reports p-values for the Harvey, Leybourne, and Newbold (1998) MHLN statistic, which is a one-sided (upper-tail) test. Panel A and B respectively report the testing results for the null hypothesis: (1) the LMF forecasting model encompasses the GMF forecasting model; (2) the GMF forecasting model encompasses the LMF forecasting model.

Table 6: Excess Bond Return Predictions: Model Comparison

	US		UK		Japan		Germany	
	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$
Panel A: the CP factor								
$rx_t^{(2)}$	36.3***	-1.86	17.2***	1.03	36.0***	0.63	33.4***	2.45
$rx_t^{(3)}$	31.8***	-0.29	21.2***	1.43	31.0***	0.71	29.3***	2.84
$rx_t^{(4)}$	21.3***	-1.27	18.1***	1.58	27.5***	0.88	24.9***	2.98
$rx_t^{(5)}$	13.8***	-2.04	13.8***	1.76	21.8***	0.96	20.5***	2.81
Panel B: The GMF and CP factors								
$rx_t^{(2)}$	[41.7]***	0.78	[32.3]***	2.37	[42.2]***	0.81	[48.3]***	2.60
$rx_t^{(3)}$	[35.9]***	1.32	[31.0]***	2.51	[38.1]***	0.98	[45.6]***	2.38
$rx_t^{(4)}$	[24.5]***	1.35	[24.5]***	2.29	[37.3]***	1.13	[36.8]***	2.43
$rx_t^{(5)}$	[16.3]***	1.16	[16.5]***	2.14	[32.2]***	1.27	[28.5]***	2.32
Panel C: the global CP factor								
$rx_t^{(2)}$	25.9***	0.69	30.5***	1.15	14.3***	0.78	20.7***	0.57
$rx_t^{(3)}$	25.5***	0.73	22.6***	2.44	14.6***	0.65	21.4***	0.82
$rx_t^{(4)}$	26.8***	0.64	12.8***	2.42	12.7***	1.14	18.5***	0.33
$rx_t^{(5)}$	20.0***	0.70	4.52***	1.78	11.7***	1.23	14.6***	0.26
Panel D: The GMF and global CP factors								
$rx_t^{(2)}$	[37.6]***	1.93	[36.3]***	3.27	15.8***	0.87	[34.7]***	3.35
$rx_t^{(3)}$	[34.2]***	1.74	[25.7]***	3.35	{16.7}***	0.35	[30.8]***	2.33
$rx_t^{(4)}$	[29.8]***	2.08	[14.1]***	3.37	{14.0}***	1.27	[25.4]***	2.91
$rx_t^{(5)}$	[24.2]***	1.77	5.41***	3.05	[16.5]***	0.34	[20.3]***	2.62

The table reports the out-of-sample R^2 statistics for log excess bond returns on the n-year long-term Treasury bond over the 1992:01-2014:12 forecast evaluation period. Utility gain (Δ) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of two would be willing to pay to have access to the forecasting model. Panels A, B, C and D respectively present the results for the forecasting models with the CP factor, the CP and GMF factors, the GMF, as well as the GMF and global CP factors as predictors. For computing utility gain, the weight on long-term bonds in the investor's portfolio is restricted to lie between zero and 1.5 (inclusive). Statistical significance for the out-of-sample R^2 is based on the p-value for the Clark and West (2007) out-of-sample MSPE-adjusted statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. "[ ]" means that the two-predictor model significantly outperforms the (global) CP-factor only model at the 5% significance levels.

Table 7: Bond Return Predictability: The Risk-Premium Factor and GMF

	$rx_t^{(2)}$		$rx_t^{(3)}$		$rx_t^{(4)}$		$rx_t^{(5)}$	
	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$
$\widehat{cf}_t$	11.5***	0.79	12.6***	0.84	12.2***	0.78	11.7***	0.85
$\widehat{cf}_t + LMF$	18.2***	1.38	14.7***	1.09	14.1***	1.19	16.2***	1.07
$\widehat{cf}_t + GMF$	[24.5]***	1.62	[20.3]***	1.38	[18.6]***	1.53	[18.3]***	1.52

The table reports the out-of-sample R^2 statistics for log excess bond returns on the n-year long-term Treasury bond over the 1992:01-2014:12 forecast evaluation period. Utility gain (Δ) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of two would be willing to pay to have access to the forecasting model. Statistical significance for the out-of-sample R^2 is based on the p-value for the Clark and West (2007) out-of-sample MSPE-adjusted statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. "[ ]" means that the two-predictor model significantly outperforms the risk-premium factor model at the 1% significance level.

Table 8: Excess Bond Return Predictions: 3-month-ahead Results

	US		UK		Japan		Germany	
	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$
Panel A: the LMF								
$rx_t^{(2)}$	5.1***	-0.99	25.5***	1.63	7.9***	1.03	20.3***	-1.02
$rx_t^{(3)}$	4.7***	0.45	19.6***	1.93	8.7***	1.07	20.1***	-0.78
$rx_t^{(4)}$	4.4***	0.66	12.3***	1.60	7.8***	1.23	17.1***	-0.20
$rx_t^{(5)}$	3.2***	0.57	4.7***	1.21	6.1***	1.64	13.4***	-0.13
Panel B: the GMF								
$rx_t^{(2)}$	7.9***	0.42	28.9***	1.91	-2.3	1.25	29.6***	1.33
$rx_t^{(3)}$	7.0***	0.86	20.1***	2.11	1.4	0.76	25.8***	1.69
$rx_t^{(4)}$	5.5***	1.24	13.0***	2.05	1.9	0.15	21.1***	1.25
$rx_t^{(5)}$	3.7***	1.49	4.3***	2.20	3.0	0.00	16.7***	1.94

The table reports the out-of-sample R^2 statistics for log excess bond returns on the n-year long-term Treasury bond over the 1992:01-2014:12 forecast evaluation period. Utility gain (Δ) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of two would be willing to pay to have access to the forecasting model. Panels A and B respectively present the results for the forecasting model with the LMF and GMF as predictors. For computing utility gain, the weight on long-term bonds in the investor's portfolio is restricted to lie between zero and 1.5 (inclusive). Statistical significance for the out-of-sample R^2 is based on the p-value for the Clark and West (2007) out-of-sample MSPE-adjusted statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Forecasts of International Bond Risk Premia

	Australia		Canada		New Zealand		Switzerland	
	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$
Panel A: the CP factor								
$rx_t^{(2)}$	32.8***	1.56	7.14***	0.56	0.35*	-0.73	40.7***	0.15
$rx_t^{(3)}$	33.6***	1.03	1.16**	0.67	2.87***	-0.65	33.5***	0.47
$rx_t^{(4)}$	27.4***	1.38	-5.27***	0.69	2.81***	-0.61	26.9***	0.83
$rx_t^{(5)}$	21.3***	1.89	-15.3***	0.72	2.37***	-0.57	20.4***	0.96
Panel B: the GMF								
$rx_t^{(2)}$	16.3***	0.87	12.6***	0.57	10.5***	0.75	6.43***	0.19
$rx_t^{(3)}$	11.2***	1.13	6.18***	0.72	17.6***	0.98	4.37***	0.58
$rx_t^{(4)}$	6.65***	1.52	1.71***	0.86	16.2***	1.14	3.54***	0.42
$rx_t^{(5)}$	1.23***	1.68	-2.35***	1.01	13.4***	1.47	1.76***	0.37
Panel C: The GMF and CP factors								
$rx_t^{(2)}$	[36.6]***	1.86	[17.3]***	0.60	[13.8]***	0.55	{42.1}***	0.25
$rx_t^{(3)}$	[37.5]***	1.95	[7.45]***	0.78	[18.7]***	0.78	[35.5]***	0.82
$rx_t^{(4)}$	{29.2}***	1.71	[-0.63]***	0.92	[18.8]***	0.80	26.3***	0.91
$rx_t^{(5)}$	21.1***	2.32	[-8.37]***	0.98	[15.3]***	0.84	12.9***	0.87

The table reports the out-of-sample R^2 statistics for log excess bond returns on the n-year long-term Treasury bond over the 2000:01-2014:12 forecast evaluation period. Utility gain (Δ) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of two would be willing to pay to have access to the forecasting model. Panels A, B, and C respectively report the results for the forecasting models with the CP factor, the GMF, and the two factors together as predictive factors. For computing utility gain, the weight on long-term bonds in the investor's portfolio is restricted to lie between zero and 1.5 (inclusive). Statistical significance for the out-of-sample R^2 is based on the p-value for the Clark and West (2007) out-of-sample MSPE-adjusted statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. "{ }" and "[ ]" mean that the two-predictor model significantly outperforms the CP-factor only model at the 5% and 1% significance levels.

Table 10: Excess Bond Return Predictions: In-sample Analysis

	US		UK		Japan		Germany	
	R^2(%)	Δ(%)	R^2(%)	Δ(%)	R^2(%)	Δ(%)	R^2(%)	Δ(%)
Panel A: the LMF								
$rx_t^{(2)}$	21.0	-0.27	3.4	1.21	11.7	0.66	19.1	0.72
$rx_t^{(3)}$	19.5	0.39	3.8	0.72	12.8	0.30	16.6	1.49
$rx_t^{(4)}$	16.2	0.55	3.9	1.09	10.6	-0.09	13.8	1.22
$rx_t^{(5)}$	14.8	0.50	3.7	1.69	10.2	0.33	11.4	0.83
Panel B: the GMF								
$rx_t^{(2)}$	15.9	-0.79	15.2	2.85	13.3	0.43	24.9	2.68
$rx_t^{(3)}$	13.8	0.73	11.4	2.23	12.9	0.57	21.6	2.73
$rx_t^{(4)}$	11.5	0.62	8.2	1.76	8.9	-0.28	18.2	1.95
$rx_t^{(5)}$	5.8	0.65	4.5	2.03	5.8	0.46	13.9	1.51
Panel C: the first PC of international real-time macro factors								
$rx_t^{(2)}$	23.1	-1.28	20.8	1.46	19.4	1.80	24.2	2.62
$rx_t^{(3)}$	21.0	1.17	17.8	2.12	19.1	0.20	21.1	2.83
$rx_t^{(4)}$	19.2	1.30	15.7	2.18	16.5	-0.90	18.2	2.10
$rx_t^{(5)}$	16.5	0.74	14.6	2.61	16.1	-0.94	16.2	1.52

The table reports the in-sample adjusted R^2 statistics for log excess bond returns on the n-year long-term Treasury bond over the 1982:01-2014:12 forecast evaluation period. Utility gain (Δ) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of two would be willing to pay to have access to the forecasting model. Panels A, B and C respectively present the results for the forecasting model with the LMF, the GMF, the first principle component of international macro factors as predictors. For computing utility gain, the weight on long-term bonds in the investor's portfolio is restricted to lie between zero and 1.5 (inclusive).

Table 11: Excess Bond Return Predictions: the Role of the United States

	UK		Japan		Germany	
	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$
Panel A: lagged US bond risk premia						
$rx_t^{(2)}$	-0.71**	0.28	-1.83***	0.38	5.25***	-0.10
$rx_t^{(3)}$	1.31***	0.60	-0.05	0.15	8.56***	-0.08
$rx_t^{(4)}$	2.05***	0.54	-0.03	0.00	8.82***	-0.06
$rx_t^{(5)}$	2.11***	0.71	-0.03	0.00	8.72***	-0.03
Panel B: US macro factors						
$rx_t^{(2)}$	-2.81	0.35	-2.21	-0.20	3.92***	-1.41
$rx_t^{(3)}$	-8.37	0.21	-0.72**	-0.41	0.86**	-1.07
$rx_t^{(4)}$	-12.6	0.55	1.13***	0.55	-1.12	-0.63
$rx_t^{(5)}$	-14.5	0.98	1.42***	0.67	-2.65	-0.42

The table reports the out-of-sample R^2 statistics for log excess bond returns on the n-year long-term Treasury bond over the 1992:01-2014:12 forecast evaluation period. Utility gain (Δ) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of two would be willing to pay to have access to the forecasting model. Panels A and B respectively present the results for the forecasting models with lagged US bond risk premia and US LMP as predictors. For computing utility gain, the weight on long-term bonds in the investor's portfolio is restricted to lie between zero and 1.5 (inclusive). Statistical significance for the out-of-sample R^2 is based on the p-value for the Clark and West (2007) out-of-sample MSPE-adjusted statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 12: Stock Return Predictions: LMF and GMF

	LMF		GMF	
	$R^2_{OS}(\%)$	$\Delta(\%)$	$R^2_{OS}(\%)$	$\Delta(\%)$
Germany	-0.95***	-0.27	0.23**	0.86
Japan	-0.51**	-0.19	-0.10	0.23
UK	-0.33**	0.01	0.87**	0.61
US	0.09*	0.42	0.93**	0.91

The table reports the out-of-sample R^2 statistics for stock returns over the 1992:01-2014:12 forecast evaluation period. Utility gain (Δ) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of two would be willing to pay to have access to the forecasting model. For computing utility gain, the weight on long-term bonds in the investor's portfolio is restricted to lie between zero and 1.5 (inclusive). Statistical significance for the out-of-sample R^2 is based on the p-value for the Clark and West (2007) out-of-sample MSPE-adjusted statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 13: Carry Trade Return Predictions

	$R^2_{OS}(\%)$	t-value	$\Delta(\%)$
Carry trade for portfolio 2	0.56	1.67	1.03
Carry trade for portfolio 3	0.87	1.84	0.54
Carry trade for portfolio 4	1.79	2.14	0.78
Carry trade for portfolio 5	1.23	2.01	0.62

The table reports the out-of-sample R^2 statistics for carry trade returns on the currency portfolios over the 1993:12-2014:12 forecast evaluation period. Utility gain (Δ) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of two would be willing to pay to have access to the GMF. Column "t-value" reports the Clark and West (2007) out-of-sample MSPE-adjusted statistic for testing the statistical significance of out-of-sample R^2.

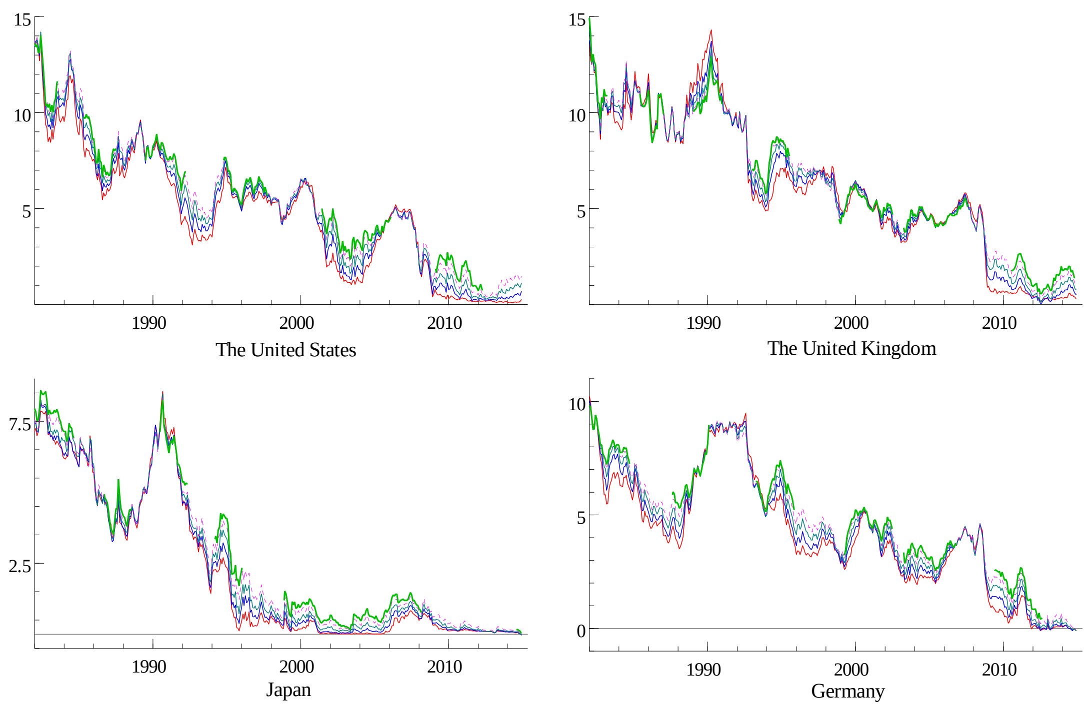

Figure 1: **Time Series of International Treasury Bond Yields**. The monthly yields plotted in these panels include, (from the lowest to the highest line, with occasional cross-overs), the one-, two-, three-, four-, and five-year interest rates. Bond yields are expressed in percentage points per annum. The data samples range from 1982:01 to 2014:12.

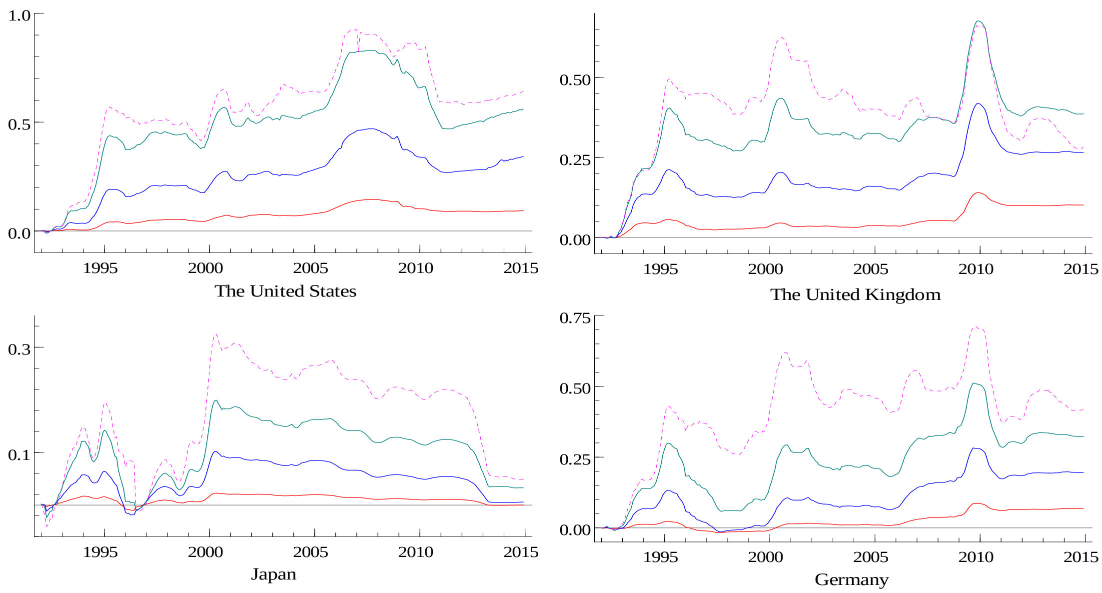

Figure 2: **Cumulative Square Prediction Errors**. The figure plots the CSPEs of the predictive model using the GMF to predict international bond risk premia against the historical average. The out-of-sample period is 1992:01-2014:12.

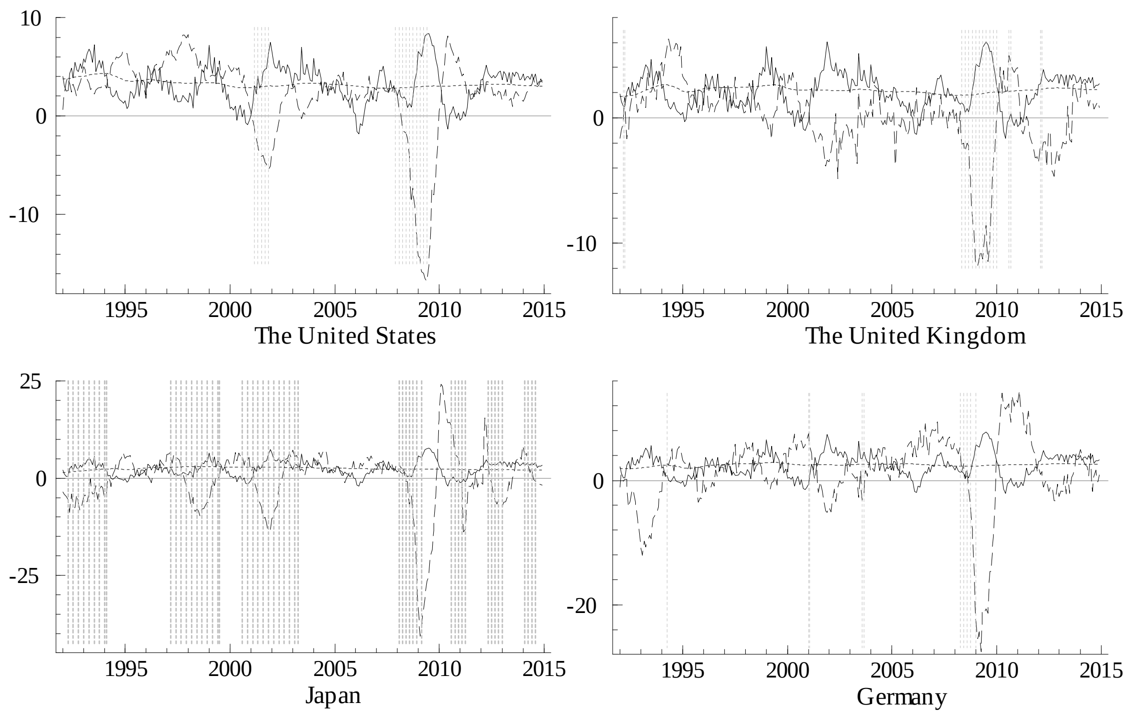

Figure 3: Bond risk premium of the 5-year bond and IP growth. The fiure plots the year-over-year industrial production growth (the dashed lines), the bond risk premium (the solid lines) predicted by the GMF, and the bond risk premium implied by the historical average (the dotted line). The shaded bars indicate economic recessions. The out-of-sample period is 1992:01-2014:12.