Decomposing Global Yield Curve Co-Movement *

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Abstract

This paper studies the co-movement of global yield curve dynamics using a Bayesian hierarchical factor model augmented with macroeconomic fundamentals. Our data-driven approach is able to pin down the drivers of yield curve dynamics and produce plausible term premium estimates. We reveal the relative importance of global shocks through two transmission channels: policy and risk channels. Global inflation is the most important core macro fundamental affecting international yields, operating through a policy channel. Two identified global yield factors significantly influence global yield co-movements through a risk channel.

Keywords: Global Yield Curves, Co-Movement, Transmission Channels, Global Macro Fundamentals, Global Latent Factors, Bayesian Factor Model.

JEL Classification Codes: C11; C32; E43; F3; G12; G15.

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1 Introduction

Understanding the underlying forces behind international bond yield curves is an important topic, and relevant economic questions are of great interest for both practitioners and researchers. How much of the variance in global bond yield co-movement is driven by global factors? Are global factors more readily identifiable as macro fundamentals or latent information? Moreover, is it worthwhile extending the potential macroeconomic explanations for global yields beyond inflation and economic growth? By answering these questions, we contribute to the literature that reveals the relevance of macro fundamentals to the term structure from a domestic and, increasingly, from an international perspective.[1] Our empirical framework builds on a factor model which has been a natural methodology for investigating the drivers of global yield curves; see, for instance, Diebold, Li and Yue (2008) and Jotikasthira, Le and Lundblad (2015). Diebold, Li and Yue (2008) indicate that the first latent factor in US, UK, German and Japanese yields is correlated with G7 inflation and the second latent factor in yields is correlated with G7 economic growth. Jotikasthira, Le and Lundblad (2015) combine latent factors and macro fundamentals to explain yields, suggesting global inflation and the US level factor explain over 70% of UK and German yields.

Our approach provides a new perspective on the analysis of international bond yield co-movement and determinants. Firstly, in order to model the term structures of seven advanced economies on a global scale, we extend the dynamic hierarchical factor model of Moench, Ng and Potter (2013) and explicitly incorporate global macro variables. We consequently identify latent factors in an international yield curve model using an efficient one-step estimation procedure that accommodates information in global macro

[1] Our empirical evidence suggests a high degree of homogeneity among country-specific yield factors. From a macroeconomic perspective such explanations include the role of US as safe asset provider (Gourinchas and Jeanne, 2012; Rey, 2016), less flexible exchange rate regimes (Obstfeld and Taylor, 2003; Rey, 2016), and integrated financial markets (Obstfeld and Taylor, 2003; Rey, 2016).

fundamentals. This allows us to be agnostic and assess in a data-rigorous way whether macro fundamentals, latent information, or both, drive yields at the international level.[2] Secondly, and as alluded to by Piazzesi and Schneider (2007), it may be important to consider an extended group of potential determinants to explain yield movements. We extend the set of potential economic explanations beyond the conventional inflation and economic growth. In particular, we assess the relevance of sentiment and economic uncertainty for yields, consistent with the work of Kumar and Lee (2006), Bansal and Shaliastovich (2010), Benhabib and Wang (2015) and Bloom (2014).

Our results parallel and extend the work on the determinants of international yield co-movement from Diebold, Li and Yue (2008) and Jotikasthira, Le and Lundblad (2015). We find that two global yield factors can explain, on average, more than 60% of bond yields' variance across seven countries, and country-specific components contribute to most of the remaining variance. Global inflation and a global Level factor explain over 70% of the co-movement. Our empirical results suggest macro-finance alternatives to traditional macroeconomic determinants, like sentiment and economic uncertainty, contain information in global latent yield factors to a certain extent.

In the spirit of Wright (2011) and Jotikasthira, Le and Lundblad (2015), we perform a simple but informative decomposition of two transmission channels. These channels contribute to co-movement in the global term structures of interest rates. The first channel is a central bank *policy channel*, which reflects the expectation of future short rates and has a strong link to global inflation. Our empirical evidence highlights that the importance of the policy channel increased during the global financial crisis, potentially because of a strong policy reaction in this period. The second channel is a *risk compensation channel*,

[2]Our hierarchical model has three levels. At the global level, we allow global macroeconomic fundamentals to interact with global bond factors. At a lower level, national bond factors are driven by global bond factors and country-specific components. At the lowest level, the term structure of each country is driven by national bond factors and idiosyncratic noise.

which reflects yield term premia and can be mostly explained by the global Level factor.[3] Our results indicate that the global risk premia is mainly driven by two global latent yield factors in the last 20 years.

Our proposed model has several salient features. The model-implied global short rate expectations do not violate the zero lower bound (ZLB) without imposing any hard restrictions, as we employ a plausible identification strategy for the underlying interest rate dynamics. Our results are robust to alternative specifications. With the augmentation of global macro fundamentals, our results are not sensitive to the number of yield factors specified in our model. We extend Moench, Ng and Potter (2013) by introducing an unrestricted covariance matrix in the global dynamics, which allows us to better incorporate time-series information while maintaining a good cross-sectional fit. Moreover, to characterize the time-varying dynamics and deepen our understanding, a straightforward extension with stochastic volatility is also considered.

The structure of the paper is as follows. In Section 2, we introduce the model and describe the identification and estimation issues. In Section 3, we describe the data for the G7 countries. In Section 4, we report our core empirical results. In particular, we decompose the yield co-movements into two transmission channels and highlight the roles of global inflation and the global latent factor. In Section 5, we assess the correlations between the global latent factors and measures of sentiment and economic uncertainty. We also extend the model to allow for stochastic volatility and test an alternative econometric specification. In Section 6, we conclude and summarize the implications of this analysis.

[3] Jotikasthira, Le and Lundblad (2015) emphasize the risk channel significantly impacts US, UK and German yields, using the data before the 2008 global financial crisis.

2 The Global Yield Curve Model

To analyze global bond yields, we adopt a dynamic factor model that is augmented with macroeconomic fundamentals. At the international level, there are two dynamic factor model approaches one can follow: the panel specification of Kose, Otrok and Whiteman (2003) and the hierarchical specification of Moench, Ng and Potter (2013).[4] We adopt the latter hierarchical factor structure because there are fewer parameters to estimate and this results in greater estimation efficiency. A low dimension vector of factors is used in this structure, making it attractive for bond yield modeling. Moreover, we extend both Kose, Otrok and Whiteman (2003) and Moench, Ng and Potter (2013) by allowing the dynamic factors to interact with each other at the global level.

2.1 Model Setup

Following and extending the bond yield factor structure of Joslin, Priebsch and Singleton (2014) and Coroneo, Giannone and Modugno (2015), our model for global bond yields X_{ibt} can be written as:[5]

[4] In their studies, Kose, Otrok and Whiteman (2003) identify regional factors that are uncorrelated with the global factors, while Moench, Ng and Potter (2013) aim to find the global factors driving the regional factors. In fact, the two frameworks are compatible and Moench, Ng and Potter (2013) can be considered nested in the Kose, Otrok and Whiteman (2003) specification.

[5] Joslin, Priebsch and Singleton (2014) and Coroneo, Giannone and Modugno (2015) allow the bond yields to be loaded onto the contemporaneous yield factors only. From a modeling perspective, this condition is merely a commonly-used econometric restriction for a more parsimonious specification. The economic implication in our context is set out in the online appendix for interested readers. We test the robustness of our results to an alternative specification in Section 5.3.

$$X_{ibt} = \Lambda_{ib}^F F_{bt} + e_{ibt}^X, \tag{2.1}$$

$$F_{bt} = \Lambda_b^G G_t + e_{bt}^F, \tag{2.2}$$

$$\begin{bmatrix} G_t \\ \\ M_t \end{bmatrix} = \psi^G \begin{bmatrix} G_{t-1} \\ \\ M_{t-1} \end{bmatrix} + u_t, \tag{2.3}$$

in which the subscript i indicates the maturities of bond yields, the subscript b indicates the countries and the subscript t indicates periods of time. In the model above, Λ_{ib}^F, Λ_b^G and ψ^G are model parameters, and e_{ibt}^X, e_{bt}^F and u_t are error terms. Note that each element in e_{ibt}^X and e_{bt}^F follows a first order autoregressive process and is cross-sectionally independent, but we do not assume cross-sectional independence for the covariance matrix of u_t. In the country-level Equation (2.1), X_{ibt} represent the bond yield of country b at maturity i, and F_{bt} are the latent yield factors of country b. In Equation (2.2), G_t are the latent global yield factors that drive the national yield factors F_{bt}. Finally, Equation (2.3) describes the interactions between the yield factors and the global macro fundamentals M_t using a vector autoregression (VAR).[6]

After some algebra, our system can be rewritten as the following simple equation showing that bond yield variance is driven by three levels of innovations:

$$X_{ibt} = f_{ibt}^G(G_{t-1}, M_{t-1}, u_t) + f_{bt}^F(e_{bt}^F) + e_{ibt}^X, \tag{2.4}$$

where f^G and f^F are linear functions which can be mapped from the coefficients of our model. In our model, we include four global macro variables extracted from national data: the monetary policy rate, inflation, real activity and financial conditions, such that M_t is a 4×1 vector. The former three are standard macro fundamentals in term structure

[6]When referring to global macro fundamentals, 'fundamental' and 'factor' are used interchangeably in this paper.

modeling; see, for example, Ang and Piazzesi (2003). This also means that the nominal short rate follows a Taylor-type rule in our model structure. Additionally, we include financial conditions because liquidity and credit risk measures are suggested by Dewachter and Iania (2012).

Parameter Specification Following Moench, Ng and Potter (2013), we assume that the prior distribution for all factor loading coefficients is Gaussian, and the prior distribution for the univariate variance parameters is a scaled inverse chi-square distribution.[7] For the factor-augmented vector autoregression (FAVAR) of global dynamics we use Minnesota priors described in Koop and Korobilis (2009), where the initial condition is of the form $\boldsymbol{\alpha} \sim N\left(\mu^{MIN}, V^{MIN}\right)$ and V^{MIN} is a diagonal matrix with element $V_{i,j}^{MIN}$ given by the following:

$$V_{i,j}^{MIN} = \begin{cases} \underline{a}_1/p^2, & \text{for coefficients on own lags} \\ (\underline{a}_2\sigma_{ii})/(p^2\sigma_{jj}), & \text{for coefficients on lags of variable } j \neq i \\ \underline{a}_3\sigma_{ii}, & \text{for coefficients on exogenous variables} \end{cases}, \tag{2.5}$$

where p is the lag and σ_{ii} and σ_{jj} are the error variances estimated by standard OLS.[8] The above conjugate priors simplify the estimation problem, both mathematically and computationally. We then set out the details about our model structure as follows.

Firstly, for computational convenience, the bond yields for a specific country are stacked in the vector X_{bt} and associated innovations are stacked in the vector e_{bt}^X, following the same dynamic representation described by Equation (2.1). We treat each block (denoted as b) as one of the seven countries we consider, so $b = 1, 2, ..., 7$. For each

[7]The specified prior distributions are $N(0,1)$ and Scale-inv-$\chi^2(0.4, 0.1^2)$ for loading and variance parameters, respectively.

[8]The prior mean vector μ^{MIN} is set to $\mathbf{0}_{KM}$, and hyperparameters $\underline{a}_1$, $\underline{a}_2$ and $\underline{a}_3$ are set to 0.01, 0.01 and 100, respectively.

country, we use the yield data of 11 different maturities ($i = 1, 2, ..., 11$) and assume that 2 factors can explain most of the yield variance. The data will be discussed in Section 3.

Secondly, stacking up F_{bt} and e^F_{bt}, respectively in Equation (2.2) across seven countries produces a $K^F \times 1$ vector F_t and e^F_t. Note that $K^F = \sum_{b=1}^{B} k_b$ where k_b is the number of factors for country b, and $F_t = \Big(F_{1t}\ F_{2t}\ ...\ F_{Bt}\Big)'$ where $B = 7$.

Lastly, for the global factor dynamics described by Equation (2.3), we specify $u_t \sim N\Big(\mathbf{0}, \Sigma^{G^*}\Big)$, where Σ^{G^*} is the variance-covariance matrix of u_t and is unconstrained. Σ^{G^*} need not be a diagonal matrix in this model, as the previous literature indicates that global factors play an important role in driving bond yields,[9] and therefore, the unconstrained specification gives sufficient flexibility in exploring the global dynamics. This motivates the identification of global shocks, which will be discussed in Section 2.2. The evolution of the global factors displayed here uses only one lag for simplicity, although in practice, more lags can be used to estimate the factor dynamics. The Equation (2.3) is actually a FAVAR system, and the estimates of this system will be used for the identification of shocks and other structural analyses.

The model is completed by specifying the dynamics of idiosyncratic and country-specific components e^X_{bt} and e^F_t as follows:

$$e^X_{bt} = \Psi^X_b e^X_{b,t-1} + \epsilon^X_{bt}, \tag{2.6}$$

$$e^F_t = \Psi^F e^F_{t-1} + \epsilon^F_t, \tag{2.7}$$

where Ψ^X_b is an $N_b \times N_b$ diagonal coefficient matrix, Ψ^F is a $K^F \times K^F$ diagonal coefficient matrix, the innovations $\epsilon^X_{bt} \sim N\Big(\mathbf{0}, \Sigma^X_b\Big)$ and $\epsilon^F_t \sim N\Big(\mathbf{0}, \Sigma^F\Big)$.[10] Before we proceed with the estimation scheme, the model parameters are summarized for better illustration. Collect $\{\Lambda^F_1, ..., \Lambda^F_B\}$ and Λ^G into $\mathbf{\Lambda}$, $\{\Psi^X_1, ..., \Psi^X_B\}$, Ψ^F and ψ^G into $\mathbf{\Psi}$, and $\{\Sigma^X_1, ..., \Sigma^X_B\}$, Σ^F, Σ^{G^*}

[9] This point will also be shown in Table 1 in Section 4.1.

[10] $\Sigma^X_b = \text{diag}\big((\sigma^X_{b,1})^2, ..., (\sigma^X_{b,N_b})^2\big)$ and $\Sigma^F = \text{diag}\big((\sigma^F_1)^2, ..., (\sigma^F_{K^F})^2\big)$.

into $\mathbf{\Sigma}$. To sum up, the parameters we need to estimate are $\mathbf{\Lambda}$, $\mathbf{\Psi}$ and $\mathbf{\Sigma}$.

Remarks A key feature of our model is to augment the VAR system of global yield factors with global macro factors M_t. By extending the 'Dynamic Hierarchical Factor Model' proposed by Moench, Ng and Potter (2013), the proposed model captures the interdependencies among global macro variables and pricing factors. The dynamics of the global factors are characterized by an unrestricted FAVAR model. Factor augmentation has various advantages, as suggested by Bernanke and Boivin (2003), which are important in the context of this paper. Global macro factors are incorporated to provide an economic interpretation of yield movements and exploit the underlying dynamics. Moreover, incorporating the information drawn from a large set of variables is helpful to negate the potential non-fundamentalness of the VAR, as suggested by Fernández-Villaverde and Rubio-Ramírez (2007) and Leeper, Walker and Yang (2013). The extended version of the hierarchical model is denoted as a 'Fundamentals-Augmented Hierarchical Factor Model'. Technical details of our model are summarized in the online appendix.

Our model has a similar structure to Diebold, Li and Yue (2008) but contrasts in that we consider both latent and macro fundamentals in a one-step approach. A one-step Bayesian technique provides more accurate estimates for the following reasons. Diebold, Rudebusch and Aruoba (2006) and De Pooter (2007) provide evidence that a one-step approach produces more effective estimates. Two-step estimation introduces bias if it does not fully consider the dynamics of the factors at a higher level. As shown in the previous literature, directly introducing macro fundamentals can provide a meaningful narrative which delineates the macro shocks that drive global term structures. Our hierarchical one-step framework allows us to jointly estimate the global yield factors and country-specific components, and hence builds upon the contribution of Bauer and Diez de los Rios (2012), Abbritti et al. (2013) and Jotikasthira, Le and Lundblad (2015). Identification schemes of macro shocks can be directly introduced in this one-step approach and posterior coverage intervals are readily available, without running additional regressions that can potentially introduce bias.

2.2 Identification

In the following section, we will discuss 1) the cross-sectional restrictions for factor identification, 2) the Bayesian estimation strategy and 3) the shock identification scheme.

Nelson-Siegel (Cross-Sectional) Restrictions To identify the global factors, a standard approach is to use the principal component method, but this is nonparametric and may not fully reveal underlying time-series dynamics or structural shocks at a global level. We aim to estimate the factors using the full likelihood of the dynamic factor model, but the factors are not identifiable without appropriate restrictions. To deal with such identification issues, many authors use zero restrictions on the factor loadings; see Moench, Ng and Potter (2013). Such restrictions are only of a statistical nature, meaning they aid identification but may lead to factor estimates that are empty of structural information. To tackle this issue, we impose restrictions implied by the dynamic Nelson-Siegel (NS) term-structure model. The loadings of country-level factors are exactly the same as in Diebold, Li and Yue (2008) without estimation. The NS identification scheme is popular in term structure modeling, and we choose this scheme to fix ideas.[11]

We follow Diebold, Li and Yue (2008) closely in imposing cross-sectional restrictions.

[11] The details of the restrictions can be found in the online appendix. The two schemes, Diebold, Li and Yue (2008) and Moench, Ng and Potter (2013), share similar results. In fact, the identified factors from two schemes are nearly identical subject to rotations. For more information regarding factor identification we refer the reader to Bai and Wang (2015).

For the sake of parsimony, we only specify two global factors in total (Level and Slope) but also due to the evidence in Bauer and Hamilton (2015) that only the Level and the Slope factors are robust predictors of excess bond returns. This specification is also supported by the study of Jotikasthira, Le and Lundblad (2015). Moench (2012) and Abbritti et al. (2013) posit that an additional factor (Curvature) is helpful in revealing the term premium dynamics. Indeed, without macro information the term premium dynamics in our sample vary substantially once a third Curvature factor is added. However, we find that adding global macro fundamentals ensures that the term premium dynamics are not sensitive to the number of factors.[12] This is due to the nature of our identification strategy that the identified factors incorporate the time-series information of global macro fundamentals. These fundamentals are weakly identified from bond yields, but are helpful in characterizing plausible global dynamics when included.

Bayesian Estimation We rely on Markov Chain Monte Carlo methods (MCMC) for parameter estimation and inference. To be more specific, a simple extension of the Gibbs sampling algorithm in Carter and Kohn (1994) is proposed; we start the estimation with the initial values of $\{F_{bt}\}$ and G_t produced by the principal component method and the observed values of M_t. In the Gibbs sampling, we drop $50,000$ burn in draws and then save every 50th of the remaining $50,000$ draws. These 1000 draws are used to compute posterior means and standard deviations of the factors. We ensure the Markov chains have converged by performing standard convergence diagnostics.

As we have mentioned previously, the elements of $\mathbf{\Lambda}$ and $\mathbf{\Psi}$ are set to have normal priors, and $\mathbf{\Sigma}$ follow inverse gamma priors. Given the conjugacy, the posterior distributions

[12] The results are qualitatively and quantitatively similar even if we consider richer specifications with more factors. We also conduct a formal test proposed by Bai and Ng (2007) to determine the number of factors and use the Bayesian Information Criteria (BIC) for lag selections. The results are consistent with our specification, which are available upon request.

are not difficult to compute. Regarding the factors G_t and F_t, we follow Carter and Kohn (1994) and Kim and Nelson (1999) to run the Kalman filter forward to obtain the estimates in period T and then proceed backward to generate draws for $t = T-1, ..., 1$. As we have imposed hard restrictions on Λ^G and Λ_b^F, there is no need to draw these parameters in the Gibbs sampling above.

Shock Identification We identify global macro shocks using the Cholesky decomposition. The ordering of our global VAR system is the following: economic growth, inflation, the policy rate, financial condition index (FCI), Level and Slope factors. The ordering of the first three variables is standard in the related literature, for example Christiano, Eichenbaum and Evans (2005). These three are followed by FCI, Level and Slope, such that these fast-moving variables can react to the contemporaneous macro shocks of the first three variables. The Level and Slope are placed the lowest in the ordering because Hubrich et al. (2013) argue that the bond yields react immediately to policy change and liquidity conditions, but the monetary policy only reacts to asset price movements if they are prolonged. It is worth noting that we do not find a significant difference using alternative orderings.[13]

2.3 Decomposing Transmission Channels

Based on the hierarchical model structure, we employ a novel scheme to decompose the variance of long rates driven by global factors into two channels, similar to Wright (2011) and Jotikasthira, Le and Lundblad (2015). The first channel is the influence on the current short rate and expected future short rates. The current short rate and future short rate

[13]The results of alternative identification schemes such as Kurmann and Otrok (2013) and several extensions are reported in the online appendix. We value the recommendations on identification robustness from the referee. It is noteworthy that although the relative importance of global Level and Slope shocks can vary substantially in different identification schemes due to their correlations, the total shares of these two shocks are stable.

expectations are closely connected to monetary policy, so we regard this channel as the *policy channel*. The movements in the policy channel are in line with the Expectation Hypothesis. The second channel is the *risk compensation channel*, and this accounts for bond market risk compensation at longer maturities. Risk compensation is frequently called the 'term premia', which is the difference between the actual long yield and the Expectation Hypothesis consistent long yield.

More formally, we denote $y_t(\tau)$ as the global-driven yield at time t for a bond of τ-period maturity, i.e., $y_t(\tau) = f^G_{\tau bt}(G_{t-1}, M_{t-1}, u_t)$. Our decomposition can be described by the following:

$$y_t(\tau) = y_t(\tau)^{EH} + TP_t(\tau). \tag{2.8}$$

The first term on the right-hand side of Equation (2.8) is the Expectations Hypothesis (EH) consistent bond yield, which is equal to the average of expected short yields $E_t y_{t+i}(1)$. $y_t(\tau)^{EH}$ is given by:

$$y_t(\tau)^{EH} = \frac{1}{\tau}\sum_{i=0}^{\tau-1} E_t y_{t+i}(1) = f^{EH}(\mu_t), \tag{2.9}$$

where f^{EH} is a linear function, and μ_t collects the identified global macro shocks. The time-varying term premium is therefore:

$$TP_t(\tau) = y_t(\tau) - y_t(\tau)^{EH} = f^{TP}(\mu_t), \tag{2.10}$$

where f^{TP} is a linear function. In summary, the policy channel determines expected short rates while the risk compensation channel accounts for movements in the term premia. Please see the online appendix for additional technical details.

3 Data Description

We obtain monthly bond yield data from Bloomberg for seven advanced countries: Canada, France, Germany, Italy, Japan, the UK and the US. The empirical analysis focuses on government yields of eleven maturities: 3, 6, 12, 24, 36, 48, 60, 72, 84, 96 and 120 months. Our empirical model uses macroeconomic variables from Bloomberg, and indicators of financial condition from St. Louis Federal Reserve Economic Data (FRED). We construct four global macro factors using a list of macro fundamentals among the seven countries, and the fundamentals include inflation (CPI), industrial production (IP) and the change in monetary policy rates (PR). We also use a large number of country-specific financial condition indexes (FCI) to construct a global FCI. The full sample of monthly data is from December 1994 to March 2014. The details about the data are described in the Data Appendix.

Before we implement our one-step estimation, the global macro factors M_t are extracted from country-specific macro series. As mentioned above, there are four categories of country-specific macro series: economic growth, inflation, change in policy rate and financial condition index. We employ a new approach proposed by Koop and Korobilis (2014) to extract the global macro indicators from country-specific series.[14] Global FCI is correlated with financial market volatility, as various measures of the financial conditions including VIX volatility index are considered when extracting this global factor. In fact, our global FCI is significantly correlated with the dynamic variance of the first global Fama-French (Fama and French (1993)) factor $R_m - R_f$, with a coefficient of approximately 60%. Moreover, there is a significant lead-lag relationship between two series, as the correlation between the 6-month lagged series of global FCI

[14] Nevertheless, our main results are robust to the measure of global macro factors using Stock and Watson (2002) or the measure from the OECD database. Koop and Korobilis (2014) is preferred as the explanatory power of the factors for bond yields is stronger. The online appendix displays the estimated macro factors used to augment our proposed model.

and the variance of global $R_m - R_f$ is close to 90%. This suggests that the global FCI is a leading indicator of *ex post* asset market volatility and is sensitive to the changes of the market environment.[15]

4 Empirical Results

4.1 Variance Decomposition of Model Hierarchies

As mentioned above, we identify two latent pricing factors for each country, which can account for the majority of bond yield variance. The global Level factor in our model drives the national Level factors. Similarly the global Slope drives national Slope factors. Table 1 displays the importance of the global innovations ($Share_G$), country-specific innovations ($Share_F$) and idiosyncratic noise ($Share_X$) from Equation (2.3), (2.2) and (2.1) respectively, relative to the total variation in the data of each country. It is clear that the global factors explain the vast majority of country yields: $Share_G$ is greater than 0.6 for almost all countries.[16] Consequently, this characteristic leads us to believe the co-movement of international bond yields is generally very strong and dominates national or idiosyncratic movements. The evidence is consistent with the importance of the global factors found in Diebold, Li and Yue (2008) and Jotikasthira, Le and Lundblad (2015). As the global factors account for a large proportion of the information in national term structures, we are interested in the dynamics of the two global factors, Level and Slope, and seek to provide sensible economic interpretations for the factors in this study.

[15]We thank a referee for pointing this out. This finding is also consistent with the argument that the volatility of asset prices is commonly used as a measure of financial condition; see, for example, Hatzius et al. (2010). We use a 12-month rolling window to measure the variance of the Fama-French factor.

[16]The exception is Italy potentially because those yields bear higher sovereign and hence country-specific risks. Our results also suggest that the variance attributed to the global yield curve gradually increases with yield maturity, see the online appendix.

Table 1: Decomposition of Variance of Hierarchies

Country	Posterior Mean (Std. Dev.)		
	Global $Share_G$	Country $Share_F$	Idiosyncratic $Share_X$
US	0.75(0.07)	0.24(0.07)	0.01(0.00)
UK	0.85(0.05)	0.13(0.04)	0.02(0.01)
Germany	0.74(0.07)	0.22(0.06)	0.04(0.01)
France	0.76(0.07)	0.22(0.06)	0.02(0.00)
Italy	0.36(0.10)	0.63(0.10)	0.01(0.00)
Canada	0.71(0.07)	0.27(0.07)	0.02(0.00)
Japan	0.68(0.08)	0.30(0.07)	0.03(0.01)

Notes: This table summarizes the decomposition of variance for the three-level hierarchical model of bond yields. It displays the importance for yields of the global ($Share_G$), country-specific ($Share_F$) components and idiosyncratic noise ($Share_X$) using Equations (2.3), (2.2) and (2.1), respectively. The quantities are averaged over all maturities. Parentheses $(\cdot)$ contain the posterior standard deviation of shares in a specific block. Std. Dev. denotes the posterior standard deviation of the posterior mean.

Although global factors clearly dominate yields, national factors remain important. The variance explained by country-specific components (i.e., $Share_F$) is non-trivial and more than two standard deviations from zero. This implies that the sum of $Share_G$ of global factors and $Share_F$ of country-specific components account for $96-99\%$ of bond variation across all countries.[17] The idiosyncratic noise is largely irrelevant and our model is doing a good job modeling yield co-movement. It is consistent with the early evidence of Litterman and Scheinkman (1991) that two or three factors can capture most of the variation in bond yields.[18] Having identified significant co-movement in yields using a latent factor approach, we now seek to reconcile this result with macro fundamentals.

[17] In other words, the sum equals the share of variance of national yield factors. Note there is a clear distinction between national factors and country-specific components. Country-specific components are the movements in national factors that are not driven by global factors.

[18] In the online appendix, we present auxiliary analyses about global and country-level factor dynamics.

4.2 Decomposition of Macro Shocks

We begin our results with a decomposition of short yields. In Section 4.1, we show that the global yield factors account for the majority of the variance of bond yields.[19] To evaluate the relative importance of global macro fundamentals and latent factors in driving the co-movement in short rates, we further decompose the 120-month forecast error variance (FEV) of global shocks. As shown in Table 2, two global yield factors (Level + Slope) are important as they account for more than 60% of the variance for all countries. Specifically, the Level factor anchors the level of global yield curves, which can be affected by various sources.[20] Among all fundamentals, CPI accounts for a significant fraction of bond yield co-movement at 3-month maturity, contributing up to 25% of FEV of co-movement. These three global factors account for more than 80% of the variance across seven countries, which parallels the finding in Jotikasthira, Le and Lundblad (2015).

Policy and Risk Compensation Channels Country-specific policy rates are decided by national monetary authorities who may have different policy targets or be faced with idiosyncratic shocks. However, our empirical evidence suggests that monetary policies can be coordinated to respond to global inflation or other commonalities. Would this result be propagated to long yields? As discussed in the methodology section, the channel decomposition (policy and risk compensation) analysis of long yields is particularly helpful.

Figure 1 shows that US 10-year long yields are strongly driven by global co-movement. Moreover, it is highly unlikely that global-driven short rate expectations violate the zero lower bound (ZLB).[21] In this figure, the increase at the long end of the expected short

[19] There are important co-movements of yields, although the co-movements are primarily at the long end of the yield curve according to Byrne, Fazio and Fiess (2012) and Jotikasthira, Le and Lundblad (2015). Jotikasthira, Le and Lundblad (2015) suggest it is due to the uncoupling of short-term policy rates in different countries.

[20] For example, Christensen and Rudebusch (2012) indicate that quantitative easing causes declines in government bond yields.

[21] In reality, violations of the zero lower bound are possible as some rates have been negative recently.

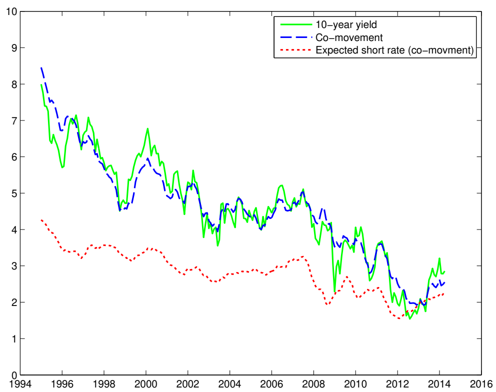
Table 2: Short Rate Variance Explained by Global Factors

Country	Posterior Mean (Standard Deviation)				
	IP	CPI	PR	FCI	Level + Slope
US	0.02(0.02)	0.22(0.12)	0.03(0.03)	0.08(0.05)	0.65(0.13)
UK	0.02(0.02)	0.24(0.12)	0.03(0.03)	0.09(0.05)	0.62(0.13)
Germany	0.02(0.02)	0.25(0.12)	0.03(0.03)	0.09(0.05)	0.60(0.13)
France	0.02(0.02)	0.24(0.12)	0.03(0.03)	0.09(0.05)	0.61(0.14)
Italy	0.02(0.02)	0.22(0.12)	0.03(0.03)	0.09(0.05)	0.64(0.14)
Canada	0.02(0.02)	0.22(0.12)	0.03(0.03)	0.08(0.05)	0.64(0.13)
Japan	0.02(0.02)	0.14(0.11)	0.02(0.02)	0.06(0.04)	0.76(0.14)

Notes: 1. This table summarizes the posterior means of the decomposition of 120-month forecast error variance of 3-month short rates driven by innovations of global yield and macro factors. In each parenthesis $(\cdot)$ the posterior standard deviation of shares in a specific block is calculated from our draws, see Section 2 for details. Larger standard deviation means higher uncertainty in the estimates, but should be interpreted with caution since the draws may not follow normal distributions.
2. IP, CPI, PR, FCI and Level + Slope denote the variance shares of shocks to global fundamentals. The global fundamentals include the industrial production growth rate (year on year, YoY), inflation, change in policy rate (YoY), financial condition index, global Level factor and global Slope factor, respectively. The shares in each row sum up to 1.
3. We employ Cholesky decomposition to identify the shocks using the following ordering: IP, CPI, PR, FCI, Level and Slope. The details can be found in the online appendix.

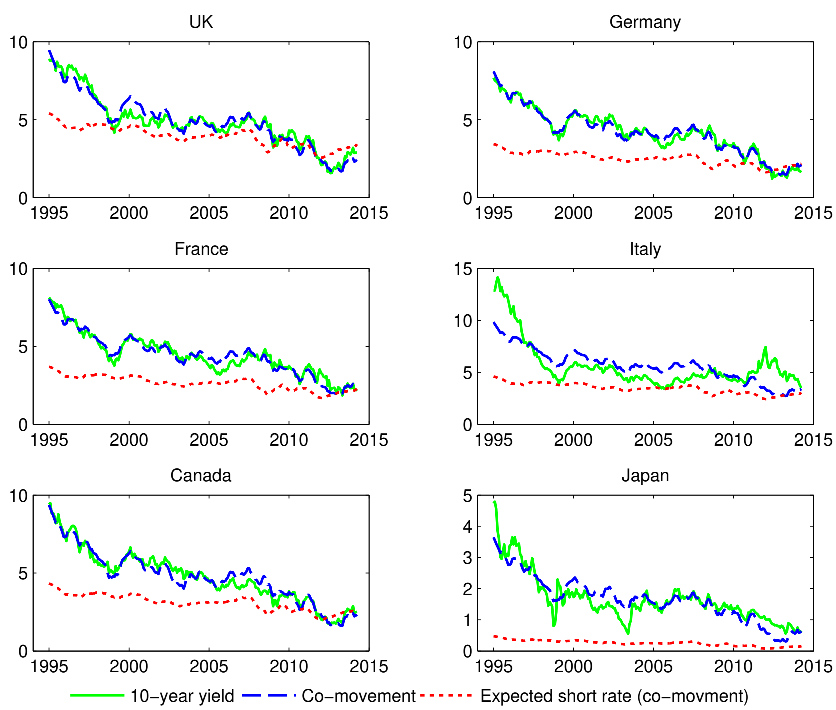
rates is related to market expectations about the policy liftoff from the ZLB, as suggested in Bauer and Rudebusch (2016). As shown in Figure 2, long yields are similarly driven by global co-movement in other G7 countries, but Italian long yields diverge from the co-movement because of the 2010-2014 sovereign debt crisis.

Figure 1: US 10-Year Bond Yields and Co-Movement



Notes: This figure shows in percentage units the observed US 10-year bond yields, the global-driven yield movements and expected short rates implied by the model. The 10-year nominal yields are plotted by the solid line. The dashed line plots the portion of yields driven by global factors (co-movement), and the dotted line is the expected short rate path.

Figure 2: 10-Year Bond Yields and Co-Movements



Notes: This figure shows in percentage units the observed 10-year bond yields, the global-driven yield movements and expected short rates of G7 countries except the US. The 10-year nominal yields are plotted by the solid line. The dashed line plots the portion of yields driven by global factors (co-movement), and the dotted line is the expected short rate path.

We firstly assess the relative importance of the policy and risk channels in driving the co-movement in long yields. Table 3 displays the proportions of long yield variance driven by global factors which are due to these channels.[22] We find that long bond co-movements are largely driven by the risk compensation channel. For all seven countries' long rates, this risk channel accounts for more than 53% of the total variance of commonalities. The relative importance of the risk compensation channel is aligned with the results in Jotikasthira, Le and Lundblad (2015).[23] As for Japan, the risk compensation channel accounts for 96% of long bond movements. The extended zero interest-rate policy in Japan potentially compresses the response of short rate expectations when faced with global shocks. Moreover, the term structure of Japanese bond yields can be very flat and therefore, the national Slope factor may not respond significantly to global Slope shocks. Note that the proportions of variance attributed to each channel are not sensitive to the variable ordering in shock identification, as the ordering can only significantly affect the variance proportion of each variable but not the sum of the variance.

[22] We focus upon 10-year yields since other long yields present similar results.

[23] Jotikasthira, Le and Lundblad (2015) indicate the risk compensation channel accounts for around 80% and 42% for the US and Germany, respectively. We include the financial crisis period in our sample; so, we have a decreased share for the US and an increased share for Germany.

Table 3: Decomposition of Long Yield Variance

Country	Channel	Fraction	Posterior Mean (Std. Dev.) IP	CPI	PR	FCI	Level + Slope
US	Policy	47%	0.02 (0.02)	0.30 (0.19)	0.04 (0.04)	0.05 (0.05)	0.60 (0.23)
	Risk Compensation	53%	0.02 (0.02)	0.14 (0.11)	0.05 (0.03)	0.09 (0.06)	0.69 (0.15)
UK	Policy	39%	0.02 (0.02)	0.32 (0.19)	0.04 (0.04)	0.05 (0.05)	0.57 (0.23)
	Risk Compensation	61%	0.02 (0.02)	0.13 (0.10)	0.05 (0.03)	0.09 (0.06)	0.72 (0.14)
Germany	Policy	23%	0.02 (0.02)	0.32 (0.19)	0.04 (0.04)	0.05 (0.05)	0.56 (0.23)
	Risk Compensation	77%	0.02 (0.02)	0.10 (0.08)	0.04 (0.02)	0.07 (0.05)	0.77 (0.11)
France	Policy	33%	0.02 (0.02)	0.32 (0.19)	0.04 (0.04)	0.05 (0.05)	0.57 (0.23)
	Risk Compensation	67%	0.02 (0.02)	0.12 (0.09)	0.04 (0.02)	0.08 (0.05)	0.74 (0.13)
Italy	Policy	29%	0.02 (0.02)	0.30 (0.19)	0.04 (0.04)	0.05 (0.05)	0.59 (0.23)
	Risk Compensation	71%	0.02 (0.02)	0.11 (0.08)	0.04 (0.02)	0.07 (0.05)	0.76 (0.12)
Canada	Policy	27%	0.02 (0.02)	0.30 (0.19)	0.04 (0.04)	0.05 (0.05)	0.59 (0.23)
	Risk Compensation	73%	0.02 (0.02)	0.10 (0.08)	0.04 (0.02)	0.07 (0.05)	0.76 (0.12)
Japan	Policy	4%	0.02 (0.02)	0.23 (0.18)	0.03 (0.04)	0.04 (0.05)	0.67 (0.21)
	Risk Compensation	96%	0.02 (0.02)	0.09 (0.08)	0.03 (0.02)	0.05 (0.04)	0.81 (0.10)

Notes: 1. This table summarizes the decomposition of 120-month forecast error variance of the 10-year bond yields driven by innovations of factors through two channels: the policy and the risk premium channels. In each parenthesis $(\cdot)$ the posterior standard deviation of shares in a specific block is calculated from our draws, see Section 2 for details. Larger standard deviation means higher uncertainty in the estimates, but should be interpreted with caution since the draws may not follow normal distributions.
2. IP, CPI, PR, FCI and Level + Slope denote the variance shares of shocks to global fundamentals. The global fundamentals include the industrial production growth rate (YoY), inflation, change in policy rate (YoY), financial condition index, global Level factor and global Slope factor, respectively. The shares in each row sum up to 1.
3. We employ Cholesky decomposition to identify the shocks using the following ordering: IP, CPI, PR, FCI, Level and Slope. The details can be found in the online appendix.

Moreover, we find that global inflation and the global Level are still the main drivers of long yields through each of the channels. The two factors together stably explain more than two-thirds of the co-movement in long yields in different identification schemes. Lastly, while future short rate expectations are significantly driven by global inflation, term premia is primarily driven by the global Level. Global inflation plays an important role through the policy channel since central banks use inflation targeting. Even when the policy rule is constrained near the zero lower bound, there can still be an adjustment to global inflation shocks through changes in expectations of future short rates.

5 Extensions and Robustness

5.1 Information in Global Yield Factors

The global Level factor is one of the most important factors driving global yield co-movement. However, its economic implications and meaning are not well understood. As shown in Figure 1, the US long rates and global co-movement are strongly correlated, which squares with several macroeconomic theories: 1) The US is the supplier of safe assets (Gourinchas and Jeanne, 2012; Rey, 2016); 2) The exchange rate adjusts so the real return of capital is equalized (ex-ante) across countries up to a premium (Obstfeld and Taylor, 2003); 3) The large contribution of global Level in the short maturities is consistent with inflation target shocks (De Graeve, Emiris and Wouters, 2009).

In this section, we go beyond traditional macroeconomic variables, and explore the information content of global Level and Slope factors that is purged of the contemporaneous correlation with macro fundamentals. We appeal to two possible explanations that are well documented in the macro-finance literature. Our first explanation is that asset prices can be driven by economic uncertainty, see Bloom (2014) for a comprehensive review. We use the US and European economic policy uncertainty indicators constructed by Baker, Bloom and Davis (2013) as the measure of economic uncertainty. The second explanation corresponds to the sentiment-based theory favored by Kumar and Lee (2006), Bansal and Shaliastovich (2010) and Benhabib and Wang

(2015). As suggested in Ludvigson (2004), the consumer confidence index is a widely used measure of investor sentiment. We obtain leading indicator aggregates of G7 from the OECD database as proxies of global sentiment, which include the composite leading indicator, business confidence index and consumer confidence index.

Table 4 reports regression results on the determinants of global co-movements. The regression of the global Level factor on global macro factors used in this paper shows that only a relatively smaller portion of variance is driven by macro factors (i.e., approximately 20%), which is consistent with our previous findings. Adding sentiment and/or economic uncertainty measures greatly increases the explanatory power, and the adjusted R^2 is increased by more than 50%. Regarding the global Slope factor, macro information and the sentiment measures can significantly increase the adjusted R^2, although the Slope factor is relatively less important in driving yield movements.

Table 4: Co-Movement Regressions

	Level				**Slope**				**TP**	$\mathbf{y^E}$
CLI^{G7}		-0.35(0.08)		-0.48(-0.01)		0.6(0.05)		0.62(0.00)	-0.17(0.00)	-0.41(-0.01)
BCI^{G7}		-0.07(0.09)		-0.07(-0.01)		-0.42(0.06)		-0.43(0.00)	-0.12(0.00)	-0.04(0.00)
CCI^{G7}		0.89(0.05)		0.47(0.08)		-0.03(0.03)		0.02(0.05)	0.27(0.04)	0.36(0.06)
PU^{US}			-0.01(0.00)	0.08(0.00)			0(0.00)	0.06(0.00)	0.04(0.00)	0.07(0.00)
PU^{EU}			-0.01(0.00)	0.06(0.00)			0(0.00)	0.05(0.00)	0.03(0.00)	0.05(0.00)
M	*	*	*	*	*	*	*	*	*	*
$adjR^2$	20.14%	65.22%	58.74%	72.96%	42.28%	60.72%	42.72%	60.80%	93.76%	83.47%

Notes: This table summarizes the regressions of global Level and Slope factors, and the US 10-year term premia (TP) and long-term short rate expectations y^E, on global macro variables, leading indicators and/or policy uncertainty indicators. M collects global macro variables used in our models. The leading indicators are G7 aggregates from the OECD database, where CLI, BCI and CCI are the composite leading indicator, business confidence index and consumer confidence index, respectively. Policy uncertainty indicators include the US policy uncertainty index PU^{US} and the Europe policy uncertainty index PU^{EU}, which are calculated by Baker, Bloom and Davis (2013). The sample is from 1994:12 to 2014:03 at monthly frequency. The standard errors are given in parentheses $(\cdot)$ and the Adjusted R^2 are reported.

In Table 4, we also report the regressions of the global-driven movements of the US 10-year bond through two channels. The results for other countries or at other maturities are very similar, as the global-driven movements of all countries are linear functions of global factors. All measures of economic uncertainty and sentiment are highly significant. This finding parallels the fast-growing literature in empirical asset pricing with the consideration of economic uncertainty or sentiment.

As we have detected that sentiment and economic uncertainty measures are closely related to global Level and Slope factors, it would be informative to gauge the contributions of sentiment and economic uncertainty. We conduct a further robustness check by replacing these two global yield factors with the information of sentiment and economic uncertainty. This is implemented in two steps. Firstly, we regress five sentiment and economic uncertainty measures on the global Level and Slope factors, respectively. The projections (fitted values) are considered to be the information of sentiment and economic uncertainty contained in global yield curves. Secondly, we replace global Level and Slope with respective fitted values (denoted $SeEcU\_L$ and $SeEcU\_S$) and execute similar econometric exercises as discussed in the previous sections.

The empirical results are shown in Table 5, which highlight that sentiment and economic uncertainty are important in driving global yield curve movements. The results again indicate that global inflation, among all variables, is the most important driver of global bond yields through a policy channel. Sentiment and economic uncertainty are the most important drivers through a risk compensation channel. In general, the results are similar to the original ones, except that the variation through the policy channel is decreased. This implies the information of global yield factors that is not attributed to sentiment and economic uncertainty is useful in forming short rate expectations.[24]

[24]We only delineate sentiment or economic uncertainty from current fundamentals and not expected future fundamentals, to the extent that there is some correlation. In fact, replacing the dynamic factors by sentiment and uncertainty as such (not fitted values) provides weaker explanatory power, possibly because useful information in these indicators is weakly spanned. We thank a referee for the insight.

Table 5: Decomposition of Long Yield Variance (Replacing Global Yield Factors)

Country	Channel	Fraction	Posterior Mean (Std. Dev.)				
			IP	CPI	PR	FCI	SeEcU_L + SeEcU_S
US	Policy	12%	0.01	0.43	0.04	0.15	0.37
			(0.00)	(0.02)	(0.00)	(0.01)	(0.04)
	Risk Compensation	88%	0.06	0.09	0.11	0.20	0.53
			(0.00)	(0.01)	(0.00)	(0.00)	(0.03)
UK	Policy	9%	0.01	0.41	0.03	0.13	0.43
			(0.00)	(0.03)	(0.01)	(0.01)	(0.04)
	Risk Compensation	91%	0.06	0.09	0.13	0.26	0.45
			(0.00)	(0.01)	(0.00)	(0.00)	(0.02)
Germany	Policy	5%	0.01	0.45	0.04	0.12	0.38
			(0.00)	(0.02)	(0.01)	(0.01)	(0.03)
	Risk Compensation	95%	0.06	0.10	0.13	0.15	0.57
			(0.00)	(0.01)	(0.00)	(0.00)	(0.02)
France	Policy	6%	0.01	0.43	0.05	0.11	0.40
			(0.00)	(0.02)	(0.01)	(0.01)	(0.04)
	Risk Compensation	94%	0.07	0.12	0.15	0.16	0.50
			(0.00)	(0.01)	(0.00)	(0.00)	(0.02)
Italy	Policy	6%	0.02	0.38	0.06	0.12	0.42
			(0.00)	(0.03)	(0.01)	(0.00)	(0.03)
	Risk Compensation	94%	0.09	0.18	0.18	0.40	0.15
			(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Canada	Policy	6%	0.01	0.43	0.03	0.15	0.38
			(0.00)	(0.02)	(0.00)	(0.01)	(0.04)
	Risk Compensation	94%	0.05	0.08	0.11	0.19	0.58
			(0.00)	(0.01)	(0.00)	(0.00)	(0.02)
Japan	Policy	0%	0.02	0.49	0.08	0.13	0.26
			(0.00)	(0.01)	(0.01)	(0.00)	(0.02)
	Risk Compensation	100%	0.06	0.09	0.12	0.28	0.45
			(0.00)	(0.01)	(0.00)	(0.00)	(0.02)

Notes: 1. This table summarizes the decomposition of 120-month forecast error variance of the 10-year bond yields driven by innovations of factors through two channels: the policy and the risk premium channels. The global yield factors Level and Slope are replaced by the information of sentiment and economic uncertainty contained in these two variables, receptively. In each parenthesis (·) the posterior standard deviation of shares in a specific block is calculated from our draws, see Section 2 for details. Larger standard deviation means higher uncertainty in the estimates, but should be interpreted with caution since the draws may not follow normal distributions.
2. IP, CPI, PR, FCI and SeEcU_L + SeEcU_S denote the variance shares of shocks to global fundamentals. The global fundamentals include the industrial production growth rate (YoY), inflation, change in policy rate (YoY), financial condition index, sentiment and economic uncertainty information contained in global Level factor and global Slope factor, respectively. The shares in each row sum up to 1.
3. For comparison, we employ Cholesky decomposition to identify the shocks using the following ordering: IP, CPI, PR, FCI, SeEcU_L and SeEcU_S.

5.2 Characterizing Stochastic Volatility

We allow for stochastic volatility in this section, which potentially helps characterize the time-varying feature of global factor dynamics. In particular, we extend our model and consider time-varying variance in Equation (2.3). That means we only need to modify the estimation algorithm at the global level, which greatly simplifies our MCMC estimation. For the sake of stability and computational tractability, we consider a constant-coefficient VAR model with stochastic volatility. This method is consistent with the findings of Carriero, Clark and Marcellino (2016) and Chan and Eisenstat (2018) that most of the fitting gains come from allowing for stochastic volatility rather than time variation in the VAR coefficients.[25]

In our extension, the covariance matrix follows an inverse-Wishart distribution. At time t, the estimate of the covariance matrix is updated according to conditional information:

$$\Sigma^{G*}|X_t, X_{t-1}, ..., X_1 \sim W^{-1}(n_t\Sigma_t^X + \Sigma_0^{G*}, n_t + \nu_0), \tag{5.1}$$

where Σ_t^X is the sample covariance estimate, n_t is the sample size, Σ_0^{G*} and ν_0 are prior parameters, which are obtained using a 2-year training sample ending at the end of 1994. The posterior mean estimator of the covariance matrix is given by

$$E[\Sigma^{G*}|X_t, X_{t-1}, ..., X_1] = \frac{n_t\Sigma_t^X + \Sigma_0^{G*}}{n_t + \nu_0 - p - 1}, \tag{5.2}$$

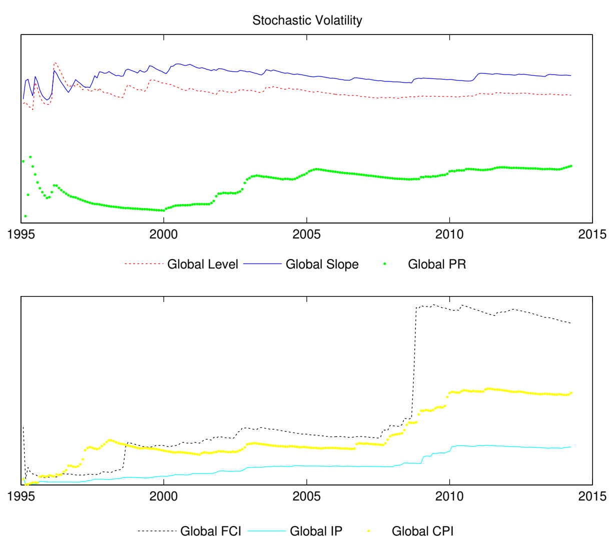
where p is the size of the covariance matrix. Following Koop and Korobilis (2013), this estimator can be approximated by an exponentially weighted moving average approach:

[25] Their models belong to the state-of-the-art literature considering factor stochastic volatility, e.g., Aguilar and West (2000), Chib, Nardari and Shephard (2002) and Kastner, Frühwirth-Schnatter and Lopes (2017), among others. We further test for time-varying coefficients, which provides no fitting gains over the constant-coefficient VAR with stochastic volatility.

$$E[\Sigma^{G^*}|X_t, \Sigma^{G^*}_{t-1}] \approx \delta^G u_t u_t' + (1-\delta^G)\Sigma^F_{t-1}, \tag{5.3}$$

where u_t is a vector of forecast errors, $\Sigma^{G^*}_{t-1}$ is the covariance estimate at time $t-1$, and δ^G is a sufficiently small scalar called 'forgetting factor'. The forgetting factor is used to discount previous information and allows us to accurately estimate the conditional covariance matrix.[26] By adding this extra estimation step to a slightly modified MCMC algorithm, we satisfactorily capture the time-varying dynamics at the global level. Figure 3 displays the estimates of stochastic volatility for global shocks, where the volatility of global FCI surges during the global financial crisis and stays at a high level afterward.

Figure 3: Stochastic Volatility of Global Shocks



Notes: The figure displays the stochastic volatility of shocks to global fundamentals.

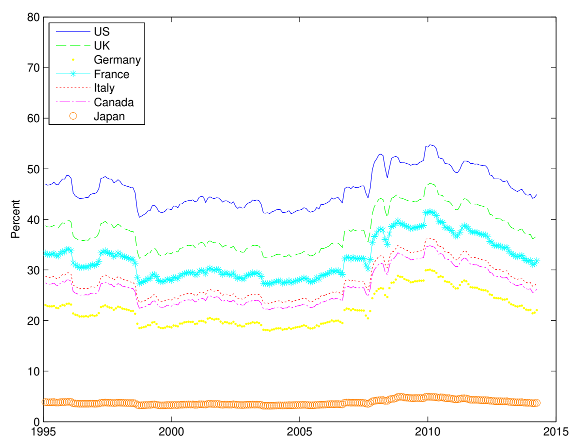
The above updating process suggests that the economic agent learns from new information and then adjusts his or her expectations when facing macro shocks. This follows Orlik and Veldkamp (2014) and they interpret the resulting changes in the variance estimates as uncertainty shocks. This argument is echoed by the recent work of

[26] We set $\delta^G = 0.05$ such that the mean of estimates of the conditional covariance matrix over the sample period matches the unconditional estimate, see Koop and Korobilis (2013) for details about the forgetting factor.

Creal and Wu (2014) in the context of yield curves, where they find that the largest impact of volatility changes has occurred in the US since the global financial crisis. However, whether these changes affect the transmission channels of global yields is a remaining question.

Using the conditional estimates of covariance, we reveal the time-varying importance of the policy channel for 10-year bonds in Figure 4. The fractions attributed to the policy channel are trending together for all countries. We do not observe rapid changes in the fractions for each country during the sample period. In the zero lower bound episode, there is a notable increase in the relative importance of the policy channel for all countries except Japan, suggesting the global co-movement is increasingly influenced by global shocks to short rate expectations. Contrary to the case in Japan, the zero interest-rate policy for the other countries does not hamper the power of global shocks in influencing the economic agent's short rate expectations.

Figure 4: Time-Varying Importance of the Policy Channel



Notes: The figure displays the fraction of long yield variance attributed to the policy channel for each G7 country over time.

Although the empirical evidence does not reveal compelling changes in the relative importance of the two transmission channels during the financial crisis, the relative importance of global shocks through each channel varies to some extent. Take the US, for example; Figure 5 sets out the three most important global shocks to 10-year yields through the policy and the risk channels.[27] Global inflation and global FCI have become more important through both channels since the global financial crisis. In particular, global inflation explains more than 40% of the variance through the policy channel during the financial crisis. In contrast, the global Level dominates throughout the whole sample period through the risk compensation channel. During the global financial crisis, global short rates were very low, reaching the zero lower bound in many countries. Consequently, the variation in short rates was relatively small, and a rule-based monetary policy tends to be constrained. As shown in Figure 2 and Table 3, Japan is unlikely to adjust expected future short rates possibly because of the prolonged zero interest-rate policy.

Figure 5: Time-Varying Importance of Global Shocks (US)

Notes: The figure displays over time the fractions of US long yields' variance attributed to shocks to global Level, inflation and FCI, through the policy and the risk compensation channels, respectively.

[27]For the other countries we have quantitatively and qualitatively similar results.

5.3 Macro-Spanning Condition

As we have discussed, a salient feature of our approach is that we introduce a flexible identification scheme robust to alternative model specifications. In particular, a seemingly 'unspanned' setup, i.e., bond yields are not loaded on contemporaneous macro factors, is employed for parsimony.[28] However, our results are not sensitive to the alternative setup. If macro information is truly spanned by bond yields, then our identified factors are naturally close to rotations of macro factors and hence can satisfactorily span the macros.

To validate the above argument, we proceed with a robustness check by allowing global macro factors to be pricing factors. Equation (2.1) now becomes

$$X_{ibt} = \Lambda_{ib}^{F} F_{bt} + \Lambda_{ib}^{M} M_t + e_{ibt}^{X}.$$

We then examine to what extent the *macro spanning condition* affects bond yields, as macro factors now have direct influence. Table 6 provides a quantitative evaluation of macro shocks in a spanned setup. Not surprisingly, spanned and unspanned setups give qualitatively indistinguishable and quantitatively similar results.

[28] The *macro spanning condition*, i.e., bond yields are loaded on contemporaneous yield and macro factors, is discussed in detail in Joslin, Priebsch and Singleton (2014) and Bauer and Rudebusch (2015), and we also discuss the economic implications in the online appendix.

Table 6: Decomposition of Long Yield Variance (Macro Spanning)

Country	Channel	Fraction	Posterior Mean (Std. Dev.)				
			IP	CPI	PR	FCI	Level + Slope
US	Policy	44%	0.02	0.31	0.04	0.05	0.58
			(0.02)	(0.19)	(0.04)	(0.05)	(0.22)
	Risk Compensation	56%	0.02	0.15	0.06	0.09	0.67
			(0.02)	(0.11)	(0.03)	(0.06)	(0.15)
UK	Policy	37%	0.02	0.32	0.04	0.05	0.56
			(0.02)	(0.19)	(0.04)	(0.05)	(0.22)
	Risk Compensation	63%	0.02	0.15	0.05	0.09	0.69
			(0.01)	(0.10)	(0.03)	(0.06)	(0.14)
Germany	Policy	16%	0.02	0.36	0.05	0.05	0.52
			(0.02)	(0.19)	(0.05)	(0.06)	(0.22)
	Risk Compensation	84%	0.02	0.10	0.05	0.07	0.76
			(0.02)	(0.07)	(0.02)	(0.04)	(0.10)
France	Policy	34%	0.02	0.30	0.04	0.05	0.59
			(0.02)	(0.19)	(0.04)	(0.05)	(0.22)
	Risk Compensation	66%	0.02	0.11	0.05	0.07	0.75
			(0.02)	(0.09)	(0.02)	(0.05)	(0.13)
Italy	Policy	29%	0.02	0.32	0.04	0.05	0.57
			(0.02)	(0.19)	(0.04)	(0.05)	(0.22)
	Risk Compensation	71%	0.02	0.11	0.04	0.08	0.75
			(0.02)	(0.09)	(0.02)	(0.05)	(0.12)
Canada	Policy	24%	0.02	0.31	0.04	0.05	0.58
			(0.02)	(0.19)	(0.04)	(0.05)	(0.22)
	Risk Compensation	76%	0.02	0.11	0.04	0.07	0.77
			(0.01)	(0.08)	(0.02)	(0.05)	(0.12)
Japan	Policy	4%	0.02	0.32	0.04	0.05	0.57
			(0.02)	(0.19)	(0.04)	(0.05)	(0.22)
	Risk Compensation	96%	0.02	0.09	0.04	0.05	0.80
			(0.02)	(0.08)	(0.02)	(0.04)	(0.11)

Notes: 1. This table summarizes the decomposition of 120-month forecast error variance of the 10-year bond yields driven by innovations of factors through two channels: the policy and the risk premium channels. The *macro spanning condition* is imposed. In each parenthesis $(\cdot)$ the posterior standard deviation of shares in a specific block is calculated from our draws, see Section 2 for details. Larger standard deviation means higher uncertainty in the estimates, but should be interpreted with caution since the draws may not follow normal distributions.
2. IP, CPI, PR, FCI and Level + Slope denote the variance shares of shocks to global fundamentals. The global fundamentals include the industrial production growth rate (YoY), inflation, change in policy rate (YoY), financial condition index, global Level factor and global Slope factor, respectively. The shares in each row sum up to 1.
3. We employ Cholesky decomposition to identify the shocks using the following ordering: IP, CPI, PR, FCI, Level and Slope. The details can be found in the online appendix.

6 Conclusion

We propose a hierarchical factor model to jointly identify global and national Level and Slope factors augmented with global fundamentals: inflation, real activity, changes in policy rate and financial conditions. Co-movement accounts for, on average, two-thirds of variability in global bond yields. Global inflation, Level and Slope shocks explain most of the global yield co-movement, through a policy channel and a risk compensation channel. Shocks to global inflation play an important role through the policy channel, especially during the financial crisis, while shocks to two global latent yield factors matter through the risk channel. Moreover, we find that the information in the global latent factors can be largely explained by measures of sentiment and economic uncertainty.

There are many possible avenues for future work. Country-specific components account for nonnegligible variance of bond yields, which are related to 'spillover effects' and are potentially caused by divergence in monetary policies or other risk factors.[29] It would be interesting to specifically evaluate to what extent spillovers across different countries contribute to bond yield movements. Motivated by our findings in this paper, it is desirable to propose a structural model with the consideration of sentiment and economic uncertainty to explain global transmissions.

[29]For example, the domestic fluctuations in the yield factors of Italian bond yields are closely related to its sovereign credit risk. Using Italy-Germany 10-year bond spread as a credit risk proxy, we discover a high correlation 0.98 between country-specific variation in the Level factor and the proxy. Using a separate dataset of Italy 5 Years Sovereign CDS (from August 2004 to April 2012), we also detect a strong positive correlation 0.96 between country-specific variation in the Level factor and CDS, as along with a strong negative correlation -0.85 between country-specific variation in the Slope factor and CDS.

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Online Appendix: Not for Publication

Appendix A Data Appendix

Table A.1: List of Financial Condition Indexes

Series ID	**Description**
STLFSI	St. Louis Fed Financial Stress Index [1]
KCFSI	Kansas City Financial Stress Index [1]
ANFCI	Chicago Fed Adjusted National Financial Conditions Index [1]
CFSI	Cleveland Financial Stress Index [1]
VIX	CBOE S&P Volatility Index [1]
BFCIUS	Bloomberg United States Financial Conditions Index [1]
BFCIEU	Bloomberg Euro-Zone Financial Conditions Index [1]
GFSI	BofA Merrill Lynch Global Financial Stress Index [1]
EASSF	Euro Area Systemic Stress Indicator Financial Intermediary [1]
WJF	Westpac Japan Financial Stress Index [1]
GSF	Goldman Sachs Financial Index [1]
BCF	Bank of Canada Financial Conditions Index [1]

Notes:
1. In square brackets [·] we have a code for data transformations used in this data set: [1] means original series is used. The series are not seasonally adjusted.
2. Data are obtained from Bloomberg, spanning from Jan. 1990 to Mar. 2014. The data may be unbalanced. The first five series can also be obtained from St. Louis Federal Reserve Economic Data (http://research.stlouisfed.org/).

Table A.2: List of Yields

Series ID	**Description**
ITA	Italy Sovereign (IYC 40) Zero Coupon Yields [1]
CAN	Canada Sovereign (IYC 7) Zero Coupon Yields [1]
FRA	France Sovereign (IYC 14) Zero Coupon Yields [1]
GER	German Sovereign (IYC 16) Zero Coupon Yields [1]
JP	Japan Sovereign (IYC 18) Zero Coupon Yields [1]
UK	United Kingdom (IYC 22) Zero Coupon Yields [1]
US	Treasury Actives (IYC 25) Zero Coupon Yields [1]

Notes:
1. In square brackets [·] we have a code for data transformations used in this data set: [1] means original series is used. The series are not seasonally adjusted.
2. Data are obtained from Bloomberg, spanning from Dec. 1994 to Mar. 2014. The yields are of the following 11 maturities: 3 months, 6 months, 1 year, 2 years, 3 years, 4 years, 5 years, 6 years, 7 years, 8 years and 10 years.
3. The zero-coupon yields are calculated step-by-step using the discount factors that are derived from standard bootstrapping, given the set of coupon bonds, bills, swaps or a combination of these instruments. A minimum of four instruments at different tenors are required for each yield curve. The bootstrapping is similar to the Unsmoothed Fama-Bliss method, see Fama and Bliss (1987).

Table A.3: List of Real Activity Indicators

Series ID	**Description**
IMFIPUS	IMF US Industrial Production SA [5]
IMFIPUK	IMF UK Industrial Production SA [5]
IMFIPJP	IMF Japan Industrial Production SA [5]
IMFIPGER	IMF Germany Industrial Production SA [5]
IMFIPFR	IMF France Industrial Production SA [5]
IMFIPITA	IMF Italy Industrial Production SA [5]
IMFIPCAN	IMF Canada Industrial Production SA [5]

Notes:
1. In square brackets [·] we have a code for data transformations used in this data set: [5] means log first-order difference (annually growth rate, YoY) is used.
2. Data are obtained from Bloomberg, spanning from Jan. 1990 to Mar. 2014. The data may be unbalanced.

Table A.4: List of CPI and Policy Rates

Series ID	**Description**
IMFCPIUS	IMF US CPI % Change in Percent per Annu [1]
IMFCPIUK	IMF UK CPI % Change in Percent per Annu [1]
IMFCPIJP	IMF Japan CPI % Change in Percent per Annu [1]
IMFCPIGER	IMF Germany CPI % Change in Percent per Annu [1]
IMFCPIFR	IMF France CPI % Change in Percent per Annu [1]
IMFCPIITA	IMF Italy CPI % Change in Percent per Annu [1]
IMFCPICAN	IMF Canada CPI % Change in Percent per Annu [1]
IMFFUNDUS	IMF US Federal Funds Rate in Percent per Annu [2]
IMFFUNDUK	IMF UK Bank of England Official Bank Rate [2]
IMFFUNDJP	IMF Japan Official Rate in Percent per Annu [2]
IMFFUNDCAN	IMF Canada Official Rate in Percent per Annu [2]
IMFFUNDEU	IMF Euro Area Official Rate in Percent per Annu [2]

Notes:
1. In square brackets [·] we have a code for data transformations used in this data set: [1] means original series is used; the series are seasonally adjusted. [2] means first-order difference (annually) is used.
2. Data are obtained from Bloomberg, spanning from Jan. 1990 to Mar. 2014. The data may be unbalanced. Specifically, in our dynamic factor extraction, the Euro Area Official Rate pre 1999 is programed to be excluded (as missing data imputed by Kalman filter) in the beginning, and then included for richer information.

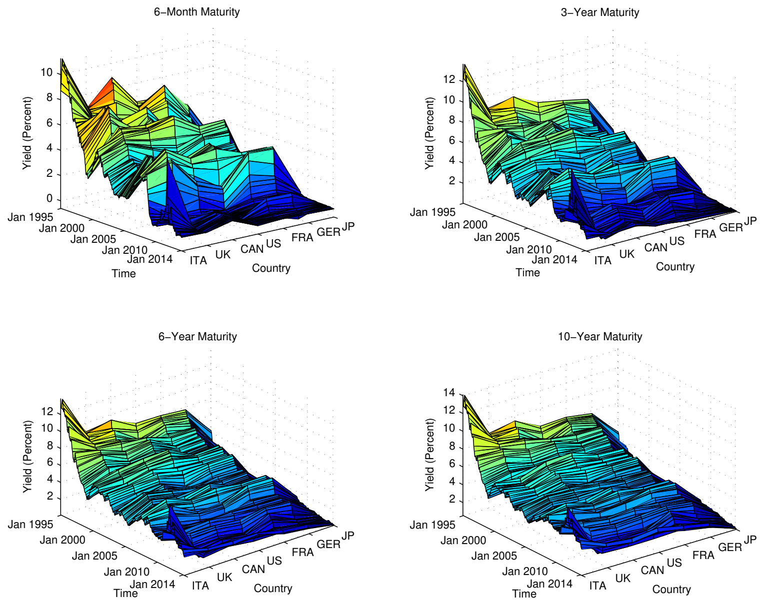
A.1 Bond Yield Statistics

Table A.5: Descriptive Statistics of Bond Yields

Country	Maturity	Mean	Std. Dev.	Min.	Max.	$\hat{\rho}(1)$	$\hat{\rho}(12)$	$\hat{\rho}(30)$
US	3	2.82	2.27	0.01	6.39	0.99	0.74	0.26
	12	3.04	2.26	0.10	7.20	0.98	0.76	0.30
	60	3.92	1.88	0.59	8.03	0.97	0.76	0.42
	120	4.57	1.45	1.54	8.00	0.97	0.72	0.43
UK	3	3.91	2.32	0.28	7.50	0.99	0.77	0.47
	12	4.00	2.36	0.12	7.45	0.99	0.77	0.48
	60	4.51	2.00	0.58	8.94	0.98	0.75	0.43
	120	4.85	1.66	1.57	8.90	0.97	0.72	0.29
Germany	3	2.49	1.52	0.00	5.14	0.98	0.66	0.27
	12	2.63	1.53	0.01	5.82	0.98	0.64	0.25
	60	3.48	1.55	0.33	7.47	0.97	0.67	0.35
	120	4.17	1.46	1.22	7.69	0.97	0.70	0.35
France	3	2.63	1.68	0.01	7.93	0.98	0.56	0.21
	12	2.76	1.66	0.02	7.04	0.97	0.58	0.22
	60	3.67	1.49	0.69	7.87	0.96	0.61	0.29
	120	4.42	1.32	1.85	8.14	0.96	0.63	0.30
Italy	3	3.44	2.58	0.28	11.00	0.98	0.63	0.24
	12	3.73	2.50	0.60	11.74	0.98	0.57	0.17
	60	4.90	2.39	1.95	14.01	0.96	0.51	0.11
	120	5.61	2.22	3.42	14.14	0.97	0.54	0.09
Canada	3	3.10	1.91	0.21	8.88	0.96	0.59	0.28
	12	3.36	1.90	0.49	8.88	0.97	0.64	0.33
	60	4.23	1.80	1.19	9.40	0.97	0.74	0.45
	120	4.75	1.69	1.72	9.48	0.97	0.74	0.41
Japan	3	0.25	0.34	0.00	2.24	0.89	0.28	0.07
	12	0.31	0.37	0.01	2.48	0.89	0.39	0.07
	60	0.91	0.66	0.13	4.07	0.92	0.57	0.17
	120	1.66	0.77	0.55	4.79	0.94	0.60	0.18

Notes: This table presents descriptive statistics for monthly yields at different maturities across G7 countries. The sample includes Italy (ITA), Canada (CAN), France (FRA), Germany (GER), Japan (JP), the UK and the US, spanning from Dec. 1994 to Mar. 2014. We use the following abbreviations. **Std. Dev.**: Standard Deviation; **Min.**: Minimum; **Max.**: Maximum; $\boldsymbol{\hat{\rho}(k)}$: Sample Autocorrelation for Lag k.

Figure A.1: Bond Yields of Seven Countries



Notes:
1. The above charts plot the bond yields for G7 countries in the sample. The sample includes Italy (ITA), Canada (CAN), France (FRA), Germany (GER), Japan (JP), the UK and the US, spanning from Dec. 1994 to Mar. 2014.
2. From top left clock-wise we have bond yields of maturities 6 months, 3 years, 10 years and 6 years.

A.2 Global Macro Factors

Table A.6: Correlations between the National Series and Global Factors

FCI	STLFSI	KCFSI	ANFCI	CFSI	VIX	BFCIUS	BFCIEU	GFSI	EASSF	WJF	GSF	BCF
Correlation	0.945	0.952	0.568	0.695	0.845	0.935	0.848	0.866	0.701	0.528	0.671	0.814

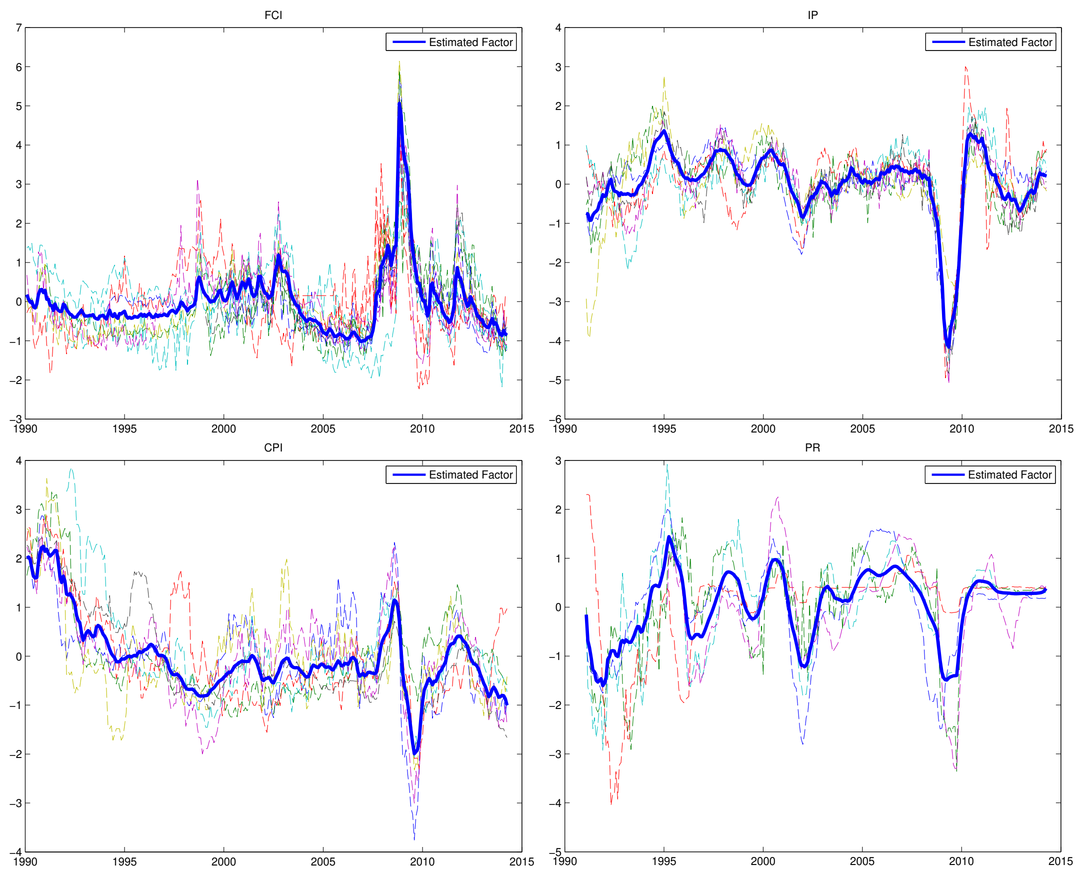
IP	IMFIPUS	IMFIPUK	IMFIPJP	IMFIPGER	IMFIPFR	IMFIPITA	IMFIPCAN
Correlation	0.899	0.889	0.767	0.831	0.940	0.946	0.731

CPI	IMFCPIUS	IMFCPIUK	IMFCPIJP	IMFCPIGER	IMFCPIFR	IMFCPIITA	IMFCPICAN
Correlation	0.805	0.810	0.761	0.525	0.887	0.891	0.739

PR	IMFFUNDUS	IMFFUNDUK	IMFFUNDJP	IMFFUNDCAN	IMFFUNDEU
Correlation	0.849	0.797	0.359	0.911	0.805

Notes: This table summarizes the correlations between the national macro series in Data Appendix and the global macro factors shown in Figure A.2, for four categories: financial condition index, industrial production growth rate (YoY), CPI and the change in policy rate (YoY).

Figure A.2: Estimated Global Macro Factors



Notes:
1. In the above charts, the thick blue lines are the global macro factors, which are estimated using the method proposed by Koop and Korobilis (2014). The Matlab code can be obtained in website https://sites.google.com/site/dimitriskorobilis/matlab/. The other thin lines with different colors are the standardized series for the estimation.
2. From top left clock-wise we have global factors of financial condition indexes, real activity, policy rates and inflation. The data used for the factor estimation are described in Appendix A, spanning from Jan. 1990 to Mar. 2014.

Appendix B Econometric Methods

In this paper we extend the hierarchical factor model of Moench, Ng and Potter (2013) by augmenting the model with macro factors. We apply the NS restrictions similar to Diebold, Li and Yue (2008) for the yield factor identification. The estimation of our model is in one step, which should provide more accurate estimates when compared to other multi-step estimations. We call the new model 'Fundamentals-Augmented Hierarchical Factor Model'.

Our proposed hierarchical model has three levels of factor dynamics, but we only focus on the global level that is augmented with global macro factors. At the global level, the dynamics of the global yield factors can be regarded as an unrestricted factor-augmented vector autoregressive (FAVAR) system. We conduct the analysis in two steps. The first step is to extract the latent global yield factors, using the proposed 'Fundamentals-Augmented Hierarchical Dynamic Factor Model'. The second step is to use the estimation results of FAVAR at the global level directly to identify the shocks of interest.

B.1 Estimation via Gibbs Sampling

A Bayesian method, i.e., Markov Chain Monte Carlo (MCMC), is used to estimate the model. A simple extension of the algorithm in Carter and Kohn (1994) is proposed here. Based on the observed values of M_t, and the initial values of $\{F_{bt}\}$ and G_t from the method of principal components, for each iteration we construct the Gibbs sampler in the following steps:

1. Draw G_t, conditional on F_t, $\mathbf{\Lambda}$, $\mathbf{\Psi}$ and $\mathbf{\Sigma}$.
2. Draw ψ^G, conditional on Σ^{G^*}, G_t and M_t.
3. Draw Σ^{G^*}, conditional on ψ^G, G_t and M_t.
4. Draw Λ^G, conditional on G_t and F_t.
5. For each b, draw F_{bt}, conditional on $\mathbf{\Lambda}$, $\mathbf{\Psi}$, $\mathbf{\Sigma}$ and G_t.
6. For each b, draw b_{th} elements of Ψ^F and Σ^F, conditional on G_t and F_t.
7. For each b, draw the Λ_b^F, Ψ_b^X and Σ_b^X, conditional on F_t and X_{bt}.

Similar to Diebold, Li and Yue (2008) and Moench, Ng and Potter (2013), the elements of $\mathbf{\Lambda}$ and $\mathbf{\Psi}$ are set to have normal priors, and $\mathbf{\Sigma}$ follow inverse gamma priors. Given the conjugacy, the posterior distributions are not difficult to compute. Regarding the factors G_t and F_t, we follow Carter and Kohn (1994) and Kim and Nelson (1999) to run the Kalman filter forward to obtain the estimates in period T and then proceed backward to generate draws for $t = T-1, ..., 1$. It is worth noting that, if we impose hard restrictions on Λ^G and Λ_b^F, then there is no need to draw these parameters in the above Gibbs sampling.

B.2 Nelson-Siegel Restrictions

Following Diebold, Li and Yue (2008), we can use two factors to summarize most of the information in the term structure of interest rates. As we show in Section 4.1, two factors have accounted for around 99% of the bond yield variance across all countries.

Below, Equation (B.1) describes how restrictions are imposed; the restrictions used in our hierarchical factor model are in fact fixing the loading of the factors. Let $y_t(\tau)$ denote yields at maturity τ; then the factor model for a single country we use is of the following form:

$$y_t(\tau) = L_t^{NS} + \frac{1 - e^{-\tau\lambda}}{\tau\lambda} S_t^{NS} + \varepsilon_t(\tau), \tag{B.1}$$

where L_t^{NS} is the "Level" factor, S_t^{NS} is the "Slope" factor, and ε_t is the error term. Additionally, λ in the exponential functions controls the shapes of loadings for the NS factors; following Diebold and Li (2006) and Bianchi, Mumtaz and Surico (2009), we set $\lambda = 0.0609$.[30]

The interpretations of Nelson-Siegel factors are of empirical significance. The Nelson-Siegel Level factor L_t^{NS} is identified as the factor that is loaded evenly by the yields of all maturities. The Slope factor S_t^{NS} denotes the spread between the yields of a short- and a long-term bond, and its movements are captured by putting more weights on the yields with shorter maturities.

The following Figure B.1 depicts the shapes of the loadings of the NS factors. In our model estimation, we fixed the Λ_b^F in Equation (2.1) by the NS loadings. We further set the Λ^G in Equation (2.2) to a diagonal matrix to identify the global factors, and the intuition behind this is that the country-level Level (Slope) factor is only driven by the global Level (Slope) factor.

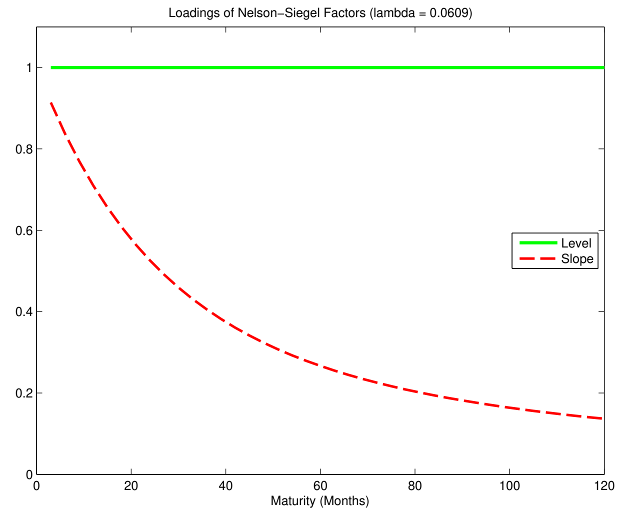
B.3 Decomposition of Variance Driven by Global Factors

The dynamics of the global factors G_t^* is given by:

$$G_t^* = \psi^G G_{t-1}^* + u_t,$$

[30] Alternatively, we can select the value of λ from a grid of reasonable values by comparing the goodness of fit. However, if we do not specify the factor dynamics and fit the Nelson-Siegel model in a static way, the selection may not be optimal. In addition, we choose a single value of λ for all the countries, as Nelson and Siegel (1987) indicate that there is little gain in practice by fitting λ individually. Therefore, we set $\lambda = 0.0609$ to fix the ideas because, 1) this value is mostly used in the related literature so revealing the dynamics of the associate latent factors is more desirable, and 2) using this value, we have a relatively better fit of the 'global short rate factor'. To ensure the robustness, we also try a grid of reasonable values; we find the results are qualitatively similar and hence our findings are robust to the selection of λ.

Figure B.1: Loadings of Nelson-Siegel Factors



Notes: The solid green line and red dashed line are the loadings for Level and Slope factors, respectively ($\lambda = 0.0609$). The horizontal axis shows the maturities of bonds, and the unit is month.

We can rewrite this as an implied Wold MA(∞) representation:

$$G_t^* = \sum_{i=0}^{\infty} \psi_i \mu_{t-i}, \tag{B.2}$$

where μ_t are the orthogonal innovations and Cholesky decomposition is needed to take into account the contemporaneous correlation of the shocks.

With simple algebra, we can write the bond yield co-movements driven by the global factors X_t^G as the following equation:

$$X_t^G = B \sum_{i=0}^{\infty} \psi_i \mu_{t-i}, \tag{B.3}$$

where B can be mapped from the loadings Λ^F in Equation (2.1) and Λ^G in Equation (2.2). The impulse response at time $t + h$ is therefore:

$$X_{t+h}^G = B \sum_{i=0}^{\infty} \psi_i \mu_{t+h-i}. \tag{B.4}$$

It is easy to have the error of the optimal h-step ahead forecast at time t:

$$X_{t+h}^G - \hat{X}_{t+h|t}^G = B \sum_{i=0}^{h-1} \psi_i \mu_{t+h-i}. \tag{B.5}$$

The mean squared error of X^G_{t+h} is given by

$$\text{MSE}(X^G_{t+h}) = \text{diag}\Big(B(\sum_{i=0}^{h-1} \psi_i \psi_i')B'\Big). \tag{B.6}$$

Therefore, the contribution of the kth factor to the MSE of the h-step ahead forecast of the yield at the jth maturity is

$$\Omega_{jk,h} = \sum_{i=0}^{h-1} R^2_{jk,i}/\text{MSE}(X^G_{t+h}), \tag{B.7}$$

where $R_{jk,i}$ is the element in row j, column k of $R_i = B\psi_i$.

Decomposition of Policy Channel and Risk Compensation Channel The policy channel is consistent with the Expectation Hypothesis (EH). The EH consistent long yield is given by

$$y_t(\tau)^{EH} = \frac{1}{\tau} \sum_{i=0}^{\tau-1} \text{E}_t y_{t+i}(1), \tag{B.8}$$

where $y_t(\tau)$ is the element of yield data X_t at maturity τ. That is to say, the EH consistent long yield is equal to the average of expected short yields $\text{E}_t y_{t+i}(1)$. If we only focus on the part driven by global factors, then after some iterations, the above equation can be written as

$$y_t(\tau)^{EH} = \frac{1}{\tau} B(I + \psi^G + \psi^{G2} + ... + \psi^{G\tau-1}) \sum_{i=0}^{\infty} \psi_i \mu_{t-i}. \tag{B.9}$$

The term premia (risk compensation channel) is given by

$$TP_t(\tau) = y_t(\tau) - y_t(\tau)^{EH}. \tag{B.10}$$

In other words, the term premia is the difference between the long yield and the EH consistent long yield. We can use similar transformations as in Equations (B.4) and (B.7) to compute the impulse response and variance decomposition of the two channels above.

Appendix C Discussion about Model Specification

C.1 Macro-Spanning Condition

Our approach is also related to the setup of Joslin, Priebsch and Singleton (2014) and Coroneo, Giannone and Modugno (2015), who impose knife-edge restrictions on the loadings of bond yields, so the macro factors cannot be inverted from yields. They denote this setting as *Unspanned Macro Risks* and argue that it is a more realistic assumption. By definition, if there exist Unspanned Macro Risks, macro factors do not directly or contemporaneously impact yields and they influence current yields only through their correlation with the yield factors.[31]

To test whether macro variables can be spanned by bond yields in our sample period, we regress inflation and industrial production on principal components (PCs) of bond yields. Table C.1 shows macro variables are weakly spanned by PCs, which parallels the finding in Bauer and Rudebusch (2015) that macro variables may not be spanned by lower-order PCs. This is because the principal component method only considers cross-section variance, see Stock and Watson (2002), and Bauer and Rudebusch (2015) suggest high-order PCs that are useful in spanning macro factors are likely to be contaminated by measurement errors.

Table C.1: Economic Measure Regressions on Bond Yield Factors

	CPI			IP		
	2 PCs	3 PCs	5 PCs	2 PCs	3 PCs	5 PCs
Global	**8.24%**	8.56%	28.63%	**7.20%**	17.05%	16.62%
US	9.88%	13.26%	38.84%	18.37%	22.07%	27.16%
UK	3.12%	2.69%	18.94%	23.12%	23.22%	56.08%
JP	-0.50%	0.07%	3.75%	3.91%	4.47%	9.28%
GER	13.03%	12.72%	32.48%	8.99%	8.63%	19.05%
FRA	2.14%	2.30%	6.74%	0.41%	0.79%	16.37%
CAN	18.37%	19.46%	38.25%	22.08%	22.15%	31.73%
ITA	17.33%	28.69%	29.66%	9.22%	8.86%	28.14%

Notes: This table reports the Adjusted R^2 of regressions in which CPI inflation and industrial production growth rate (YoY) are regressed on different numbers of principal components (PCs) of bond yields. The sample is from 1994:12 to 2014:03 at monthly frequency. The global variables are G7 aggregates from the OECD database.

Therefore, we adopt the unspanned restrictions advocated by the data for parsimony, and Bauer and Rudebusch (2015) suggest that spanned and unspanned models deliver

[31] Joslin, Priebsch and Singleton (2014) suggest that the fully spanned assumption, i.e., the macro factors can be inverted as linear combinations of yields, is often questioned and might be counterfactual. We test the robustness of our hierarchical factor model to the unspanned restriction of Joslin, Priebsch and Singleton (2014), and the results are available upon request.

similar results. It is worth highlighting the robustness of Moench, Ng and Potter (2013): Unlike principal components, this method identifies factors by allowing for not only cross-sectional variance but also time series properties. This also means, even in the extreme case that unspanned restrictions are not necessary, the identified factors will cater to the true dynamics and hence mitigate specification errors. The potential loss caused by the parsimonious unspanned setup, if any, should be economically insignificant.

Note that unspanned restrictions do not violate Taylor-type policy rules. To see this, we write down the restrictions about macro variables M_t following Bauer and Rudebusch (2015):

$$M_t = \gamma_0 + \gamma_P P_t^L + OM_t,$$

where OM_t captures the orthogonal macroeconomic variation not captured by lower-order PCs P_t^L. For convenience, assuming M_t, P_t have the same dimension and γ_P is invertible,[32] then the short rate r_t is a linear function of PCs and hence a linear function of M_t:

$$r_t = \beta P_t^L = C(\gamma_0, \gamma_P, OM_t) + \beta \gamma_p^{-1} M_t,$$

where C is a function of $(\gamma_0, \gamma_P, OM_t)$. It is clear the short rate is a linear function of macro variables.

In contrast, given the *macro spanning condition* that M_t is fully spanned, i.e., $OM_t = 0$, using only macro factors can fit the bond yields very well. If there are substantial fitting errors when we use macro factors only, we may need to reconsider the validity of this condition or incorporate latent factors.

The *macro spanning condition* should not be confused with the issue of whether bond yields are significantly driven by macro factors. That is, even if we assume macro factors are fully spanned by bond yields, macro factors do not necessarily have higher explanatory power for yields, especially when macro factors are weakly spanned by a low dimension of PCs as in Table C.1. The *macro spanning condition* is only about whether bond factors include all information of macro variables that can be used to estimate term premia, and term premia is always a linear function of macro factors in a macro-finance model, whether or not these these factors are spanned.[33]

A separate but related questions is, how much of the variance of bond yields can be explained by macro factors and why, which is what we are trying to answer in this paper. Bauer and Rudebusch (2015) explicitly indicate that 'spanned and unspanned models have identical implications for projections of macro variables on yield factors'. Following their argument, our results are considered robust with the identification strategy proposed by Moench, Ng and Potter (2013), since the pricing factors are identified allowing for time-series information of global macro fundamentals and can satisfactorily capture cross-

[32] Nevertheless, the result does not depend on the dimension of M_t or P_t^L.

[33] Macro spanning, by construction, means macro factors are a subset of pricing factors, and therefore pricing factors have all the information of macro factors. This intuition has been discussed formally in Duffee (2013).

sectional information. Moreover, our extension with an unrestricted covariance matrix of global dynamics ensures the identification of global macro shocks is not sensitive to the ambiguity about the *macro spanning condition*.

C.2 Cross-Sectional Restrictions

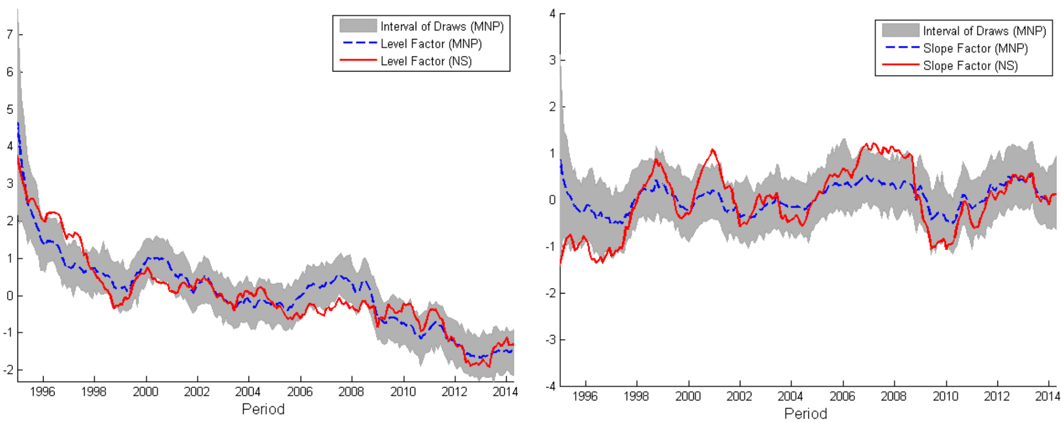
In this paper, we do not impose no-arbitrage constraints in our model as the constraints are silent about identifying the latent factors and shocks. In other words, latent factors are not identified with no-arbitrage constraints alone. Duffee (2013) suggests Nelson-Siegel restrictions are nearly equivalent to no-arbitrage in characterizing the cross-sectional information of the term structure of interest rates. Joslin, Le and Singleton (2013) show that Gaussian no-arbitrage macro-finance models are close to factor-VAR models when risk premia dynamics are not constrained. Duffee (2014) also indicates that the no-arbitrage restrictions are unimportant if a model aims to pin down physical dynamics. Since our focus here is not on the structure of risk premia dynamics, we choose to impose no such restrictions to avoid potential misspecification. The potential drawback of no-arbitrage models is that it imposes very strong restrictions on the dynamics of risk prices, to 1) ensure no-arbitrage consumption and 2) identify the model with flat likelihood. Kim and Singleton (2012) and Jotikasthira, Le and Lundblad (2015) indicate the no-arbitrage framework may generate implausible term premiums in the financial crisis.

Moreover, in an international model, arbitrage opportunities exist not only across different domestic maturities but also across different foreign assets or/and maturities due to capital controls and inflexible exchange rate regimes. Therefore, we impose Nelson-Siegel restrictions here, which provide a parsimonious structure and satisfactory performance in cross-sectional fittings of term structure, and avoids potential misspecification due to the presence of temporary arbitrage opportunities in the bond markets (Diebold, Rudebusch and Aruoba, 2006; Chen and Tsang, 2013).

Appendix D Additional Results

D.1 Comparison of Factor Indentification Schemes

Figure D.1: Identified Factors from Different Schemes (MNP vs. NS)



Notes:
1. In the above two charts, the factors identified by the scheme of Moench, Ng and Potter (2013) are plotted against the factors identified by the NS scheme of Diebold, Li and Yue (2008). To better serve the comparison purpose, the factors are extracted from a less complicated system without a macro factor augmentation.
2. The left chart shows the Level factors, while the right chart displays the Slope factors. The dashed blue lines are the median values of MNP identified factors and the gray areas cover all the draws from the MCMC estimation. The solid red lines are the median values of NS identified factors.

D.2 Co-Movement in Yields

D.2.1 Factor Dynamics

In this section, we depict the dynamics of the global yield factors estimated from our proposed 'Fundamentals-Augmented Hierarchical Factor Model'. As mentioned before, we extract two national yield factors that account for more than 96% of the variance of the term structure. We now focus on the global yield factors, as these factors typically drive the national Level and Slope factors. Firstly, we calculate the arithmetic sum of the global Level and Slope factors to evaluate the effect on the global short rate co-movement. This sum is denoted as the *global short rate factor*, and reflects the global co-movement in short rates across countries.[34] From the left panel of Figure D.2, we can see the global short rate factor is strongly correlated with the first principal component of short rates across the seven advanced economies, also implying that our model successfully captures the global co-movement of the short rates.[35] One feature of the movements of the global short rate factor is that it falls sharply after the Global Financial Crisis, consistent with a global expansion in monetary policy.

It is straightforward to decompose the global short rate factor into the global Level and Slope. The movements of these two factors are shown in the right panel of Figure D.2, in which we also highlight some distinct historical events: January 1999 and the start of the euro area, US recessions in 2001 and 2008 as defined by NBER and the European sovereign debt crisis. As we have already discussed, Level and Slope factors control the shape of the term structure, which can be informative in revealing useful macroeconomic information. For example, before 1999 there is a downward trend for the Level factor and an upward trend for the Slope factor, which means the global term structure is moving down and flattening.[36] This phenomenon indicates a moderation in global term structure, possibly caused by greater integration.[37] We can observe two clear trends abstracting from temporary disturbances in the factors. Firstly, the downward-trending global Level seems to relate to the decreasing inflation level in the period of the Great Moderation, as suggested by Evans and Marshall (2007) and Koopman, Mallee and Van der Wel (2010).

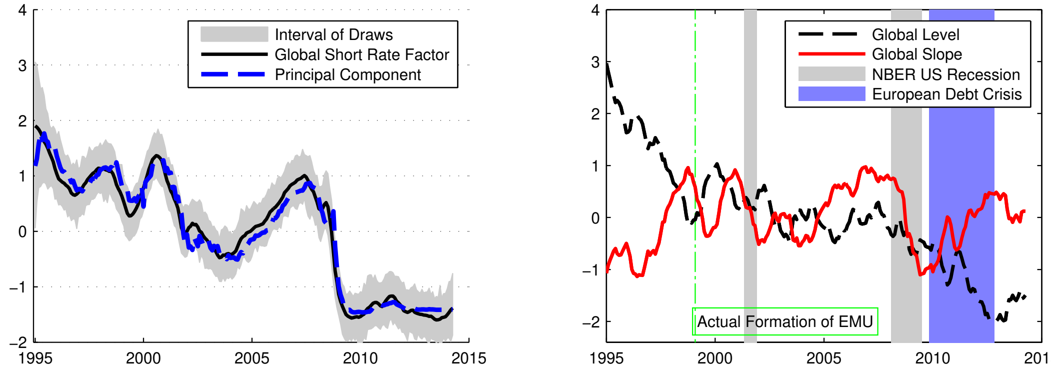
[34] By NS restrictions, for a bond at very short maturity, we have the equation that $\textit{short rate} = \beta_1 L_t^{NS} + \beta_2 S_t^{NS}$, where the loadings equal to one, i.e., $\beta_1 = \beta_2 = 1$. Therefore, the short rate is directly driven by the sum of two factors in our model construction, see Appendix B.2 for details.

[35] Note that there is a smaller proportion of bond yield movements at the country level that are not captured by the global yield factors. We find that these country-specific movements in national yield factors can be largely explained by the divergence of monetary policy in different countries. The results are consistent with the findings in Jotikasthira, Le and Lundblad (2015), but not shown here as we focus on the global co-movement.

[36] An increase in the level factor is consistent with higher yields on average. An increase in the slope factor is consistent with a flatter yield curve. In an extreme case, if two factor are moving in opposite directions but with the same magnitude, then the short rates stay still and long rates are driven by the changes in the Level factor.

[37] The strong negative correlation between the Level and Slop disappears after 1999 and reappears after the financial crisis.

Figure D.2: Global Short Rate Factor and the Decomposition



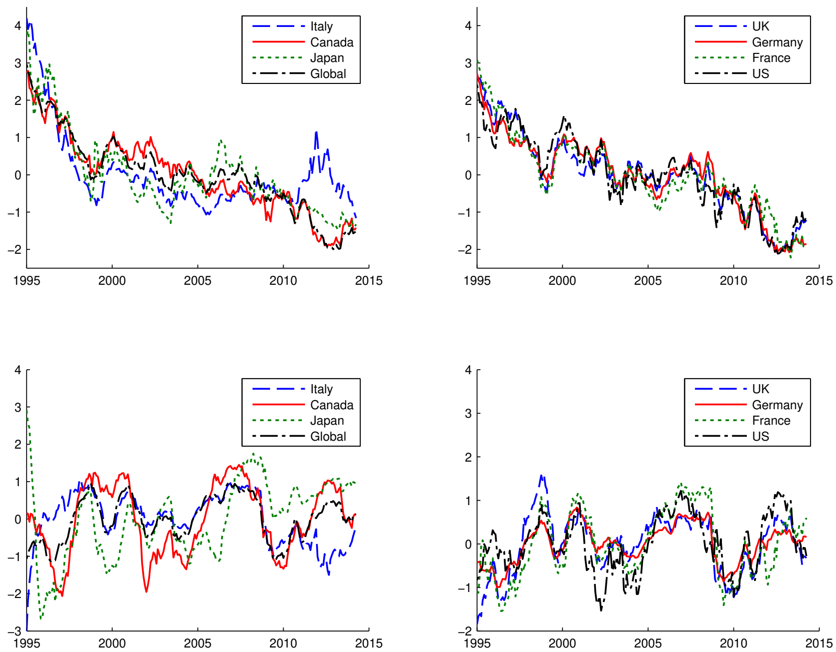
Notes: 1. The left panel shows the global short rate factor (i.e., an arithmetic sum of extracted global Level and Slope factors) and the first principal component of the national short-run policy rates (dashed line). The first principal component of national policy rates accounts for more than 84% of total variance of national policy rates. The gray areas cover all the draws of the global short rate factor (i.e., Level + Slope) from our model, and the solid black line is the median value of the draws. Data standardization allows the factors to fall below zero.
2. The right panel shows the decomposition of the median of the global short rate factor. We decompose the short rate factor into the global Level (dashed line) and the global Slope (solid red line). In general, the Level factor controls the level of the term structure whereas the Slope factor controls the slope of the term structure. The shaded areas cover some major recession periods in the US and Europe.

Secondly, the Slope factor is declining during US recessions, suggesting it is related to real economic activity, as indicated in Kurmann and Otrok (2013).

D.2.2 Commonality of Level and Slope

We firstly plot our identified Level and Slope factors in Figure D.3, respectively, to evaluate the commonalities in country-level yield factors. The Slope factors are relatively less persistent than the Level factors. From the figures, it is evident that a strong co-movement in Level factor dynamics exists, but some also exists for the Slope. We also calculate the communality statistics for all countries in Table D.1 to better quantify matters; i.e., we calculate the proportion of national level or slope factor explained by the global equivalent. This indicates that the commonality in Level factor dynamics is stronger but co-movement remains in the Slope. Generally, we find significant co-movement among Germany, France, Canada, UK and US. In contrast, the Level and Slope factors of Italy are relatively more divorced from the global factors, consistent with Table 1 above; the Japanese Slope factor is much less common among all Slope factors as the communality statistic is nearly zero. The above findings are reassuringly in line with the results in Diebold, Li and Yue (2008).

Figure D.3: Estimated Global and National Factors



Notes: The upper panels show the median values of global Level and the national Level factors. The lower panels show the median values of global Slope and the national Slope factors.

Table D.1: Communality Table of Level and Slope

Level		Slope	
Country	Communality	Country	Communality
Italy	0.45	Italy	0.24
Canada	0.94	Canada	0.35
France	0.94	France	0.67
Germany	0.94	Germany	0.91
Japan	0.80	Japan	0.04
UK	0.98	UK	0.77
US	0.90	US	0.51
Average	0.85	**Average**	0.50

Notes: This table summarizes the communality statistics for G7 national Level and Slope factors. For example, the communality for a given country is interpreted as the proportion of the variation in the national Level factor explained by the global Level factor. The interpretation is likewise for the Slope communality.

D.3 Variance Decomposition across Maturities

Table D.2: Decomposition of Variance (US)

Maturity	Posterior Mean (Standard Deviation)		
(Month)	$Share_G$	$Share_F$	$Share_X$
3	0.65(0.08)	0.32(0.08)	0.02(0.01)
6	0.68(0.08)	0.32(0.08)	0.01(0.00)
12	0.71(0.08)	0.29(0.08)	0.00(0.00)
24	0.74(0.07)	0.26(0.07)	0.01(0.00)
36	0.76(0.07)	0.24(0.07)	0.01(0.00)
48	0.77(0.07)	0.22(0.07)	0.01(0.00)
60	0.78(0.07)	0.22(0.06)	0.00(0.00)
72	0.79(0.06)	0.21(0.06)	0.00(0.00)
84	0.79(0.06)	0.21(0.06)	0.00(0.00)
96	0.79(0.06)	0.21(0.06)	0.01(0.00)
120	0.78(0.07)	0.20(0.06)	0.03(0.01)

Notes: This table summarizes the decomposition of variance for the three-level hierarchical model of US bond yields. $share_G$, $share_F$ and $share_Z$ denote the variance shares at different maturities attributed to shocks ϵ_G, ϵ_F and ϵ_X, respectively. In each parenthesis $(\cdot)$ the posterior standard deviation of shares in a specific block is calculated from our draws, see Section 2 for details. Larger standard deviation means higher uncertainty in the estimates, but should be interpreted with caution since the draws may not follow normal distributions.

Table D.3: Decomposition of Variance

Maturity	UK			Germany			France		
(Month)	$Share_G$	$Share_F$	$Share_X$	$Share_G$	$Share_F$	$Share_X$	$Share_G$	$Share_F$	$Share_X$
3	0.80(0.06)	0.20(0.06)	0.01(0.00)	0.70(0.08)	0.23(0.06)	0.07(0.02)	0.66(0.08)	0.27(0.07)	0.07(0.02)
6	0.81(0.06)	0.19(0.06)	0.00(0.00)	0.71(0.08)	0.23(0.06)	0.06(0.02)	0.70(0.08)	0.28(0.07)	0.03(0.01)
12	0.83(0.05)	0.17(0.05)	0.01(0.00)	0.72(0.08)	0.23(0.07)	0.05(0.02)	0.73(0.07)	0.27(0.07)	0.00(0.00)
24	0.84(0.05)	0.14(0.05)	0.01(0.00)	0.75(0.08)	0.23(0.07)	0.02(0.01)	0.75(0.07)	0.24(0.07)	0.01(0.00)
36	0.86(0.05)	0.13(0.04)	0.01(0.00)	0.76(0.07)	0.23(0.07)	0.01(0.00)	0.77(0.07)	0.22(0.06)	0.02(0.00)
48	0.88(0.04)	0.12(0.04)	0.00(0.00)	0.77(0.07)	0.23(0.07)	0.00(0.00)	0.78(0.06)	0.21(0.06)	0.01(0.00)
60	0.89(0.04)	0.11(0.04)	0.00(0.00)	0.77(0.07)	0.22(0.07)	0.01(0.00)	0.79(0.06)	0.20(0.06)	0.00(0.00)
72	0.89(0.04)	0.11(0.04)	0.00(0.00)	0.76(0.07)	0.21(0.07)	0.02(0.01)	0.80(0.06)	0.20(0.06)	0.00(0.00)
84	0.88(0.04)	0.10(0.04)	0.01(0.00)	0.75(0.08)	0.21(0.06)	0.04(0.01)	0.80(0.06)	0.20(0.06)	0.00(0.00)
96	0.86(0.04)	0.10(0.03)	0.04(0.01)	0.73(0.08)	0.20(0.06)	0.06(0.02)	0.80(0.06)	0.19(0.06)	0.01(0.00)
120	0.80(0.06)	0.09(0.03)	0.11(0.03)	0.71(0.08)	0.19(0.06)	0.10(0.03)	0.78(0.06)	0.18(0.05)	0.04(0.01)

Notes: This table summarizes the decomposition of variance for the three-level hierarchical model of bond yields. For each country, $share_G$, $share_F$ and $share_Z$ denote the variance shares at different maturities attributed to shocks ϵ_G, ϵ_F and ϵ_X, respectively. In each parenthesis $(\cdot)$ the posterior standard deviation of shares in a specific block is calculated.

Table D.4: Decomposition of Variance (Continued)

Maturity	Italy			Canada			Japan		
(Month)	$Share_G$	$Share_F$	$Share_X$	$Share_G$	$Share_F$	$Share_X$	$Share_G$	$Share_F$	$Share_X$
3	0.31(0.09)	0.66(0.09)	0.03(0.01)	0.52(0.10)	0.36(0.08)	0.12(0.03)	0.5(0.10)	0.44(0.09)	0.06(0.01)
6	0.32(0.10)	0.67(0.09)	0.01(0.00)	0.57(0.09)	0.36(0.08)	0.07(0.02)	0.54(0.10)	0.43(0.09)	0.03(0.01)
12	0.34(0.10)	0.66(0.10)	0.00(0.00)	0.63(0.09)	0.35(0.08)	0.02(0.01)	0.60(0.09)	0.39(0.09)	0.02(0.00)
24	0.35(0.10)	0.64(0.10)	0.00(0.00)	0.70(0.08)	0.30(0.08)	0.00(0.00)	0.65(0.08)	0.31(0.08)	0.04(0.01)
36	0.36(0.10)	0.63(0.10)	0.00(0.00)	0.74(0.07)	0.26(0.07)	0.00(0.00)	0.69(0.08)	0.28(0.07)	0.03(0.01)
48	0.37(0.10)	0.62(0.10)	0.00(0.00)	0.76(0.07)	0.24(0.07)	0.00(0.00)	0.72(0.07)	0.26(0.07)	0.02(0.00)
60	0.38(0.10)	0.62(0.10)	0.00(0.00)	0.77(0.07)	0.23(0.07)	0.00(0.00)	0.75(0.07)	0.25(0.07)	0.01(0.00)
72	0.38(0.10)	0.61(0.10)	0.00(0.00)	0.78(0.06)	0.22(0.06)	0.00(0.00)	0.76(0.07)	0.24(0.07)	0.00(0.00)
84	0.39(0.10)	0.61(0.10)	0.01(0.00)	0.79(0.06)	0.21(0.06)	0.00(0.00)	0.76(0.07)	0.23(0.06)	0.01(0.00)
96	0.39(0.10)	0.60(0.10)	0.01(0.00)	0.79(0.06)	0.21(0.06)	0.00(0.00)	0.75(0.07)	0.22(0.06)	0.02(0.01)
120	0.39(0.10)	0.59(0.10)	0.02(0.00)	0.79(0.06)	0.20(0.06)	0.01(0.00)	0.73(0.07)	0.21(0.06)	0.06(0.02)

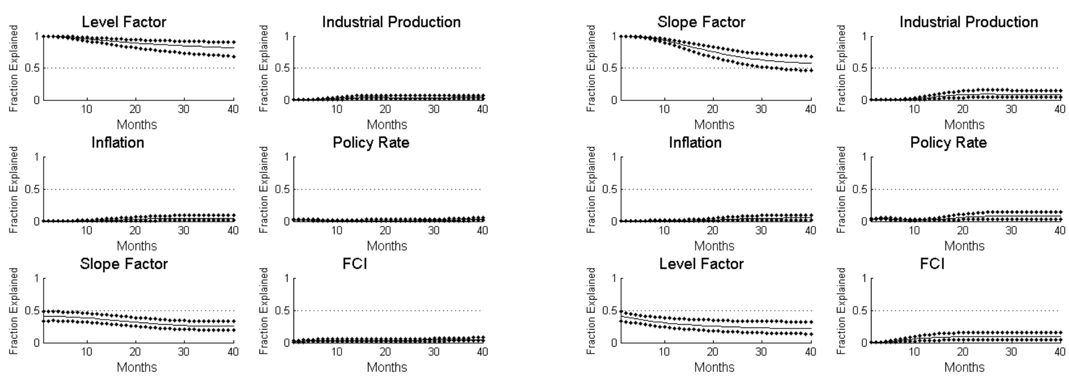
Notes: This table summarizes the decomposition of variance for the three-level hierarchical model of bond yields. For each country, $share_G$, $share_F$ and $share_Z$ denote the variance shares at different maturities attributed to shocks ϵ_G, ϵ_F and ϵ_X, respectively. In each parenthesis $(\cdot)$ the posterior standard deviation of shares in a specific block is calculated.

D.4 Shock Identification

Strictly speaking, a Cholesky identification scheme is not agnostic and therefore, a combination of sign and zero restrictions may be more suitable. To ensure the robustness of our results, we explore the relevant literature and find that employing an advanced identification scheme proposed by Uhlig (2004) and Kurmann and Otrok (2013) is particularly helpful. As indicated in Kurmann and Otrok (2013), this identification scheme is appropriate for serving our goal:'*instead of imposing zero restrictions implied by particular types of shocks and then analyzing their effects ... our identification strategy proceeds in reverse. We first uncover (in a statistical sense) the mutually orthogonal shocks that are quantitatively the most important ... and then provide an economic interpretation*.'

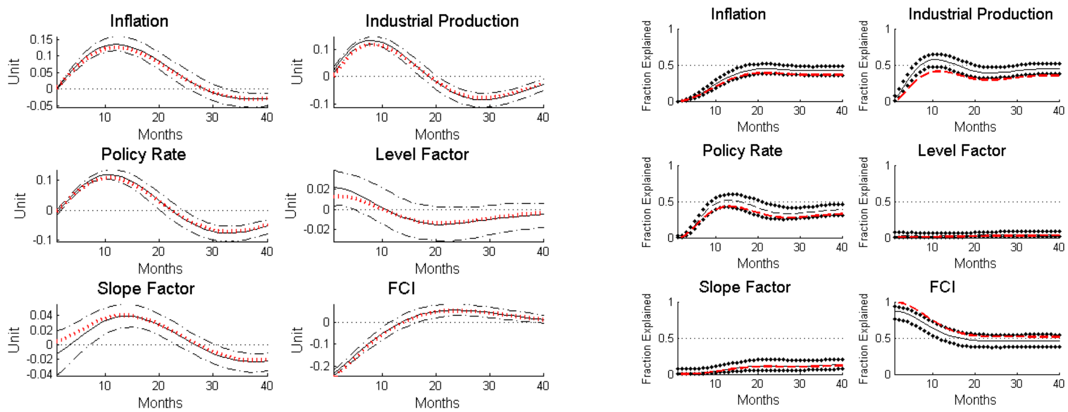
In the following Figure D.4, we identify shocks that explain the maximal amount of the Forecast Error Variance (FEV) of 'current' (i.e., in the first period) global Level and Slope factors. It is shown that these two 'current' shocks do not have significant contemporaneous impact on macro fundamentals. However, by identifying the global FCI 'current' shock, we discover this shock is closely related to the global Inflation 'future' shock (in contrast to 'current', a shock that is uncorrelated to the 'current' shock and explains the maximal amount of the 120-month FEV of a variable in the future). In the following Figure D.5, we find these two shocks are almost indistinguishable, which implies that the global FCI shock contains helpful information in predicting the variance of global inflation. A possible explanation is that the level of asset prices (jointly determined by the amount of risk and the price of risk) does not predict FCI, as FCI mainly reflects the volatility information of asset prices; this volatility information content can feed back into macroeconomy, affecting future variation in global inflation.

Figure D.4: Fraction of FEV Explained by Level and Slope Current Shocks



Notes: The solid lines in the above panels are the posterior median values. The dotted lines indicate 16 to 84 percent posterior coverage intervals. The left six panels display the Level 'current' shock and the right six panels display the Slope 'current' shock.

Figure D.5: Results for Inflation and FCI Shocks

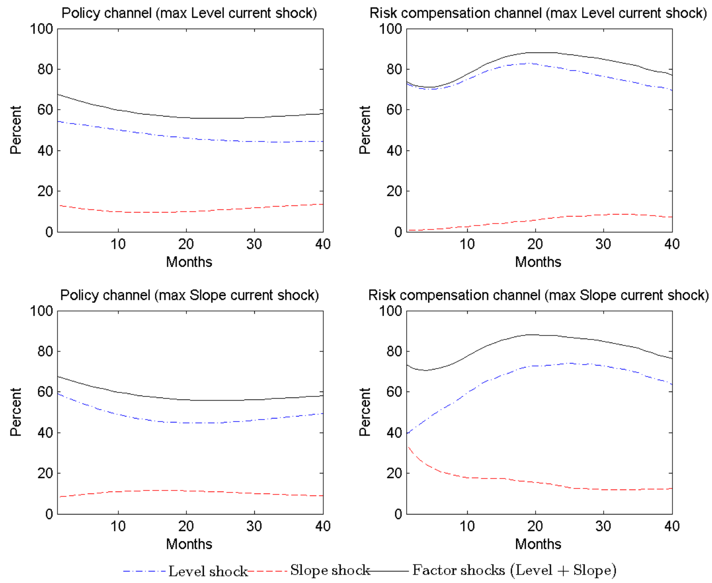


Notes: The solid lines in the above panels are the posterior median values of the inflation 'future' shock (120-month FEV), and the black dashed lines indicate 16 to 84 percent posterior coverage intervals. The red dotted lines correspond to the FCI 'current' shock. The left six panels display the impulse responses and the right six panels display the Fraction of Forecast Error Variance.

For further robustness checks, we firstly use Cholesky decomposition to identify (a) the space covered by macro shocks and then (b) the Kurmann-Otrok identification on the two-dimensional space of shocks that can be attributed to yield factors. The combination of the two identification schemes allows us to evaluate the global factor shocks (vis-à-vis global macro shocks) on the 10-year long yields (take US for example) related to the policy and risk compensation channels. We maximize the FEV of global Level and Slope, respectively. As shown in the following Figure D.6 (left panels), we find that the variance shares of US long yields explained by global factors through the policy channel are stable with different FEV-maximization implementations. In either case, the sum of factor shocks is approximately 60% by averaging across 120 periods, although for the Level and Slope factors the respective shares can vary substantially. For the risk compensation channel, the total shares of factor shocks in two cases are similar (the sum is approximately 70% on average).

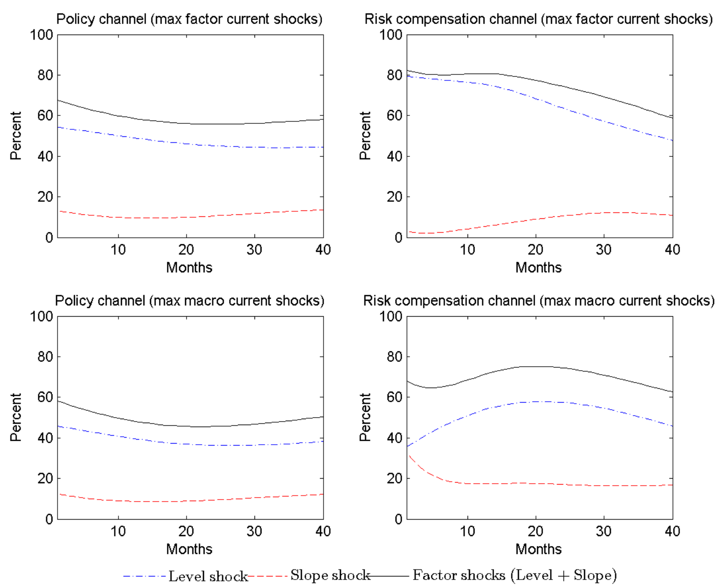
We also apply the FEV-maximization scheme to the variation of long yields and seek to maximize the long yield variance explained by 'current' shocks of either global factors or macro fundamentals. As shown in the following Figure D.7, when maximizing the yield variance explained by factor 'current' shocks, the associated factor shock share in the first period is 68%, which is obviously higher than the period-one factor shock share (58%) when maximizing the FEV explained by macro shocks. However, when averaging across 120 periods, the difference between shares in two cases decreases (less than 7%). For the risk compensation channel, the period-one shares for factors in two cases are 82% and 68%, respectively, but the averaged factor shares across 120 periods are 56% and 59%, respectively, as macro shocks identified in the latter case are less persistent.

Figure D.6: FEV-Maximization Results for Different Channels



Notes: In the upper panels we depict the US long yield variance shares explained by factor shocks when Level 'current' shock share is maximized. In the bottom panels we depict the results when Slope 'current' shock share is maximized. Note that macro share = 1 − factor share.

Figure D.7: FEV-Maximization Results for Different Channels (Continued)



Notes: In the upper panels we depict the US long yield variance shares explained by factor shocks when the sum of factor 'current' shock share is maximized. In the bottom panels we depict the results when the sum of macro 'current' shock share is maximized. Note that macro share = 1 − factor share.