

# What Does the Global Yield Curve Tell about World Economic Activity?

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Comments are welcome

## Abstract

This paper bridges the connection between the global yield curve and international economic activity. I find global yield curve factors are relevant for predicting the real growths and inflations across countries, especially at long horizon. Further, global factors play a significant role in predicting the conditional covariances of real growths and inflations across countries. I also find global factors have predictive power on international business cycle synchronization. The results seem to indicate that inflations are more internationally synchronized than the business cycles. The findings have important policy implication.

## 1 Introduction

Evidence has accumulated that a few financial variables such as interest rates and spreads have enduring power of predicting the aggregate economic activity. This predictive usefulness of interest rates and spreads thereafter has been well-established across countries. The countercyclical monetary policy accounts for at least some of the predictive power. When there is evidence of probably economic recession, the market expects the future short-term interest rate will fall, it leads to a bigger fall in long-term interest rate. The expectation thus flattens the yield curve. In bad times, investors want to escape the risk, this behavior drives up the risk premia and make risk premia also a countercyclical indicator. This is the typically heuristic explanations of where coming out of the predictive power. Estrella (2004) provides a theoretical model based on the rational expectation in an attempt to interpret relationship between the yield curve and the economic activity.

So far, empirical studies investigate the ability of yield curve as a predictor in some specific countries independently. Nevertheless few studies examine the

existence of a global yield curve that predicts the world or cross-country economic activity. The financial deregulations may increase the integration degree of financial market, in such case a global yield curve may explain most of variation of yield curves across countries. As early in 1994, Plosser and Rouwenhorst provide evidence that foreign yield curves can predict domestic economic activity at a low frequency. Diebold, Li and Yue (2007) find that there do exist the global yield curve factors. It deserves a further and full investigation of the relationship between the global yield curve and world economic activity.

From the perspective of globalization of world economy, this article tries to find some determinants of international business cycles. This is the second contribution of the paper. A large literature has provided strong evidence that there are cross-country links in macroeconomic fluctuations. Kose et al (2003) identifies a common world factor that plays an important role in explaining the variability of aggregate economic activity in most countries in a 60-country model. The common forces that induce world economic fluctuations have three major sources, respectively increasing international trade in goods and services, increasing financial asset market integration and increasing foreign direct investment (FDI). The global yield curve associated with the international financial asset trade is likely a determinant of common international business cycle factor, at least it has information about the common factor. Although a lot studies examine the driving forces from perspectives of international trade and FDI, few evidences provided from a financial market integration perspective. This is therefore a useful exercise, it contributes to the generation and propagation of international business cycle.

I use the dynamic Nelson-Siegel model from Diebold and Li (2006) to describe the dynamic evolution of yield curve. This model is neither a general equilibrium model nor a no-arbitrage model. However the forecasting performance of the model is good, in contrast, the affine term structure models, which is important for pricing interest rate derivative, forecast poorly (Duffee 2002). The dynamic Nelson-Siegel model has good performance in fitting maturity structure of yield curves, and it is extensively employed by financial institutions and central banks. Three factors of the model, respectively level, slope and curvature factors, have close interactions with macroeconomic dynamics across countries (Diebold, Rudebusch and Aruoba (2006), Tam and Yu (2008)). Simplicity is another advantage of the model. The continuous no-arbitrage model of term structure might be untractable in a big model with a lot common and idiosyncratic factors. Therefore, I use this parsimonious specification to fit the yield curves, although there is a no-arbitrage version of Nelson-Siegel model recently developed by Christen, Diebold and Rudebusch (2008).

To extract global yield curve factors, we have to depend on the country-specific factors since there is no existence of world interest rates. In this paper I follow Zhu (2008) method to filter out global factors from country-specific factors, the difference is there country factors are from arbitrage-free dynamic Nelson-Siegel model. Except global factors, there are also idiosyncratic factors driving the government bond market in each individual country. Specifically I use latent factors for Germany, Japan, U.K. and U.S. to extract global latent

factors with the Kalman filter. These global factors are used to predict the world economic activity.

The similar studies usually apply yield spreads to forecast the economic activity and inflation. I provide the evidence of forecasting usefulness of yield curve factors among countries. A comparison is made about the out-of-sample forecasting accuracy of using yield spreads and yield curve factors. The predictive power of the yield curve factors and yield spread for forecasting the real growth are country-dependent, but the yield curve is better for forecasting the inflation. For the purpose of examining the relationship of global financial variables and international business cycles, only the yield curve method is feasible now that we can't observe world interest rates.

Some major finding of the article can be summarized as follows. First I show that global yield curve factors do indeed have predictive power on real growth rate and inflation in countries investigated. The second finding is that global factors play a role in forecasting cross-country covariances of economic activity, particularly the covariances of inflations. This may imply that inflations are more synchronized than real growth, of course, real growth is a more complicated issue. The third finding is that global factors are useful predictors of world recession synchronization in a Possion regression. The recession synchronization is a count indicator, that is the sum of recession indicator of all relevant countries.

The results have straightforward policy implication. Forecasts of future path of economy is important for policy-making and bussiness decision. Businesses and policymakers would benefit from better forecasting the economic activity by taking into account the foreign yield curves since it has extra information on the domestic economic activity. This extra predictive power may come from common shocks, international trades or international portofolio diversification. The inflations seem to be more synchronized than real economic activiteis. This matter of fact has also policy implication about the direction of international policy coordination. Chiang (1997) concludes that financial integration can increase world economic welfare if and only if there is international policy coordination.

The rest of this paper is organized as follows: Data issues are summarized in section 2. Section 3 presents the dynamic Nelson-Siegel model for describing yield curves and the global yield curve model. Empirical properties and cross-country interactions of yield curves are documented. Section 4 investigates the predictive power of global yield curve. I begin this section by reviewing the forecasting ability of yield curve in each individual country, then compare the forecasting performance of yield spread and yield curve factors since previous works usually use spread as a predictor. The last subsection examines the predictive ability of global yield curve factors on world real economic growth, inflation and business cycle synchronization, the policy messege is also discussed. Section 5 concludes.

## 2 Data issues

The proxy for real economy activity is real GDP growth rates. Data on seasonally-adjusted nominal GDP and deflator for Germany, Japan, the UK, the US, is retrieved from the international financial statistics (IFS) compiled by international monetary fund (IMF). I denote the real GDP as RGDP. The annualized real growth rate from  $t$  to  $t+k$  at a quarterly frequency is constructed as follows:

$$g_{t \rightarrow t+k} = 400/k(\log RGDP_{t+k} - \log RGDP_t)$$

Consumer price index (CPI) for all countries are also from IFS. Inflation is defined by taking the yearly percentage change in the CPI index as

$$\pi_t = 100 * (\log CPI_t - \log CPI_{t-4})$$

The year-over-year real growth rate ( $g_{t \rightarrow t+4}$ ) is most frequently used index, and the predictive power of yield spread on this rate is one of most significant. I plot those growth rates across countries in figure 1. We see the comovement and heterogeneity on the economic fluctuations. There are two trends, one is the UK and the US trend, the correlation between them is 0.6370, another trend is between Germany and Japan, the correlation is 0.4545, but the cross comovement is not significant. The correlation matrix for growth rates is

$$\begin{pmatrix} g_{t \rightarrow t+4} & Germany & Japan & U.K. & U.S. \\ Germany & 1 & 0.4545 & 0.1342 & 0.1033 \\ Japan & 0.4545 & 1 & 0.0110 & 0.0181 \\ U.K. & 0.1342 & 0.0110 & 1 & 0.6370 \\ U.S. & 0.1033 & 0.0181 & 0.6370 & 1 \end{pmatrix}$$

In contrast, inflation is more homogeneous, correlations are more significant, and there seems one common trend among them, though Germany inflation comovements with other series to a less extent. In late 1980s, UK experienced relatively high inflation. On the other hand, Japan had deflation period since early 1990s, accompanying the frequent economic recession (figure 2). The correlation matrix of inflations is given below:

$$\begin{pmatrix} \pi_t & Germany & Japan & U.K. & U.S. \\ Germany & 1 & 0.5403 & 0.1981 & 0.3682 \\ Japan & 0.5403 & 1 & 0.7116 & 0.5943 \\ U.K. & 0.1981 & 0.7116 & 1 & 0.7346 \\ U.S. & 0.3682 & 0.5493 & 0.7346 & 1 \end{pmatrix}$$

The U.S. yield data consist of end-of-quarter observations of 1, 3, 6, 12, 24, 36, 60, 84, 120 months zero-coupon yields on treasury securities covering the period from January 1985 to March 2008. The data source is econstats<sup>TM</sup>. The U.K. zero-coupon yields with maturities of 6, 9, 10, 11, 12, 24, 36, 48, 60, 72, 84, 96, 108, 120 months are retrieved from econstats<sup>TM</sup>. It covers the same period as the U.S sample and all data are end-of-quarter observations. For

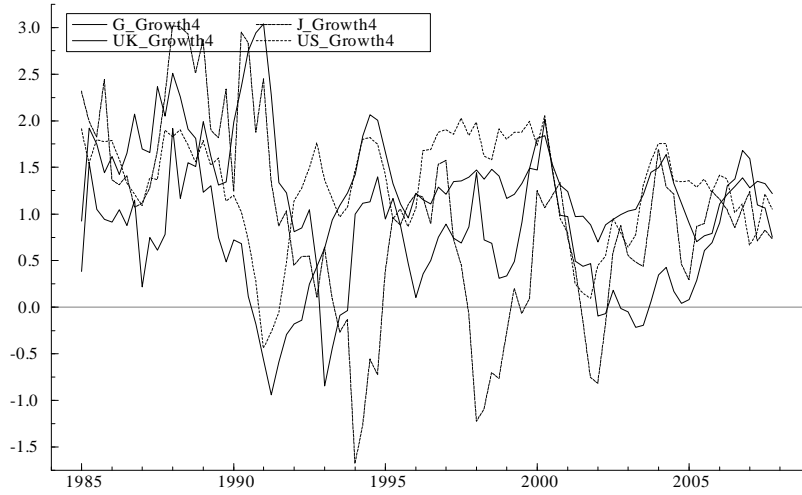


Figure 1: Year-Over-Year Real Growth Rates

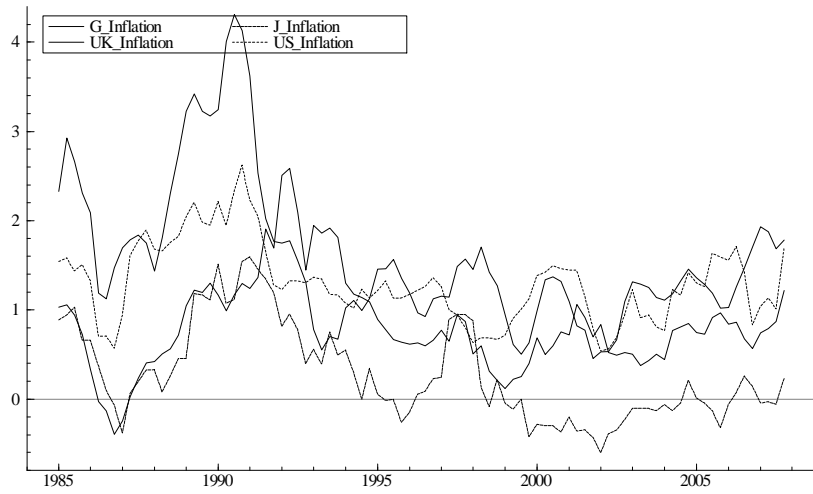


Figure 2: Year-Over-Year Inflation Rates

the Germany zero-coupon government bond yields, the quarter-end observations with maturities 12, 24, 36, 48, 60, 72, 84, 96, 108, 120 months are retrieved from Deutsche Bundesbank, the central bank of Germany.

The Japanese dataset has two sources. The first sample covering the period from January 1985 to December 1991 is from the Key Economic Statistics Files of the PACAP Database-Japan<sup>TM</sup> compiled by the Sandra Ann Morsilli Pacific-Basin Capital Markets Research Center at the University of Rhode Island. The end-of-month yields consist of government bond interest rates with maturities 12, 24, 36, 60, 84, 120 months. The second sample covers the period from January 1992 to March 2008. The dataset is downloaded from Bloomberg. The maturities are 6, 12, 24, 36, 48, 60, 72, 84, 96, 108, 120 months.

The summary statistics including skewness and kurtosis of yields for each maturity and for each country is presented in Table 1<sup>1</sup>. One stylized fact of interest rates is they tend to exhibit considerable persistence and are believed to be nonstationary or better approximated by the integrated process. This feature has profound implications for estimations and statistical inference.

Table 1 About Here

The autocorrelation coefficients and augmented Dickey-Fuller tests in Table 1 provide the evidence of persistence and non-stationarity. However, the yields are usually cointegrated, as implied by the rational expectation hypothesis. The Johansen cointegration analysis presents the evidence of common trends in yields<sup>2</sup>. The cointegration may explain another important stylized fact of the yield curve: spreads are less persistent than yields. The skewness and kurtosis show some yields do deviate considerably from the normal distribution. The standard deviations in Table 1 tells that short-term yields usually are more volatile than long-term yields with exception of Japan. For Germany, Japan and U.S., the average yield curves are upward-sloping for the time period under analysis, in contrast, the U.K. average yield curve has S-shape. Over time yield curves have many different shapes.

### 3 Yield curve models and empirical results

#### 3.1 Dynamic Nelson Siegel Model

Most of term structure models use three factors to capture stylized facts of yields in cross-section and time series. By properly restricting the factor loadings in the statistical factor model, Diebold and Li (2006) proposed the dynamic Nelson-Siegel model:

$$y_{t(\tau)} = l_t + s_t \left( \frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} \right) + c_t \left( \frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau} \right) + \varepsilon_t$$

<sup>1</sup>The statistics for Japan are based on the sample retrieved from Bloomberg. This applies to results for the Kalman filter estimates of global factors in table 3.

<sup>2</sup>The analysis results are available upon request.

where the  $l_t$  is level factor, the  $s_t$  denotes slope factor and the  $c_t$  represents curvature factor. Empirically, the level factor is corresponding to the long-term interest rates, the slope factor is associated with the difference between the short-term yield and long-term yield, the curvature factor corresponds to two times of medium-term yields minus the sum of long- and short-term yields. Therefore, the level factor is a long-term factor, the slope factor is a short-term factor and the curvature is a medium-term factor. Three factors contain information of the macroeconomic dynamics and vice versa (Diebold, Rudebusch and Aruoba(2006), Tam and Yu(2008)). The  $\lambda_t$  is the rate of changes of factors loadings along the maturity horizons, it also determines the maturity at which the curvature loading achieves its maximum.

For the entire yield curve with different maturities ( $\tau$ ) at time  $t$ , the model can be specified as:

$$\begin{pmatrix} y_t(\tau_1) \\ y_t(\tau_2) \\ \vdots \\ y_t(\tau_N) \end{pmatrix} = \begin{pmatrix} 1 & \frac{1-e^{-\lambda_t\tau_1}}{\lambda_t\tau_1} & \frac{1-e^{-\lambda_t\tau_1}}{\lambda_t\tau_1}e^{-\lambda_t\tau_1} \\ 1 & \frac{1-e^{-\lambda_t\tau_2}}{\lambda_t\tau_2} & \frac{1-e^{-\lambda_t\tau_2}}{\lambda_t\tau_2}e^{-\lambda_t\tau_2} \\ \vdots & \vdots & \vdots \\ 1 & \frac{1-e^{-\lambda_t\tau_N}}{\lambda_t\tau_N} & \frac{1-e^{-\lambda_t\tau_N}}{\lambda_t\tau_N}e^{-\lambda_t\tau_N} \end{pmatrix} \begin{pmatrix} l_t \\ s_t \\ c_t \end{pmatrix} + \begin{pmatrix} \varepsilon_t(\tau_1) \\ \varepsilon_t(\tau_2) \\ \vdots \\ \varepsilon_t(\tau_N) \end{pmatrix} \quad (1)$$

The dynamic Nelson-siegel has superior out-of-sample forecasting performance, especiall at long horizon. In constrast, some affine term structure models give poor forecasting performance (Duffee, 2002). Although the dynamic Nelson-Siegel is neither general equilibrium model nor no-arbitrage model, it provides empirical fit, simplicity and parsimony. Therefore this model is applied extensively.

If the dynamic movements of three latent factors follow a vector autoregressive process of first order as in Diebold et al (2006), the model becomes a state-space system. The state equation describing the dynamics of  $l_t, s_t, c_t$  is

$$\begin{pmatrix} l_t - \mu_l \\ s_t - \mu_s \\ c_t - \mu_c \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} l_t - \mu_l \\ s_t - \mu_s \\ c_t - \mu_c \end{pmatrix} + \begin{pmatrix} u_t(l) \\ u_t(s) \\ u_t(c) \end{pmatrix} \quad (2)$$

The measurement equation (1) and state equation (2) can be expressed in a compact form

$$y_t = \Lambda f_t + \varepsilon_t$$

$$(f_t - \mu) = A(f_{t-1} - \mu) + u_t$$

For linear least-square optimality of the Kalman filter, the disturbances are assumed to be vector white noise process and uncorrelated at all lags,

$$\begin{pmatrix} \varepsilon_t \\ u_t \end{pmatrix} = N \left[ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} R & 0 \\ 0 & Q \end{pmatrix} \right]$$

Furthermore, the disturbances are uncorrelated with the initial state,

$$E(f_0 \varepsilon'_t) = 0$$

$$E(f'_0 u'_t) = 0$$

The state-space framework is a powerful system for analysis of dynamic models. The Kalman filter can provide maximum-likelihood estimates and optimal filtered and smoothed estimates of latent factors. The dynamic Nelson-Siegel model thus enjoys the state-space representation.

### 3.2 Global yield curve model

A number of studies have focused on the international linkages of bond markets. There seems consensus that the bond yields and returns are highly correlated across countries. Hafer et. al. (1997) finds long-term yields seem to be cointegrated across countries, hence there is comovement of international bond markets. Ilmanen (1995) finds that a small set of global instruments can forecast a significant fraction of monthly yields variation, the author concludes that the predictability of global bond returns come from a few global factors. The empirical study of Driessen et. al. (2003) find the world bond markets are correlated by using a linear factor model and principle component analysis, the driving force of the comovement is the level of yields in each country, this is consistent with the matter of fact that the level factor dominates the term structure of interest rates. Engsted and Tanggaard (2007) finds the inflation news drive the comovement between the U.S. and Germany bond markets. Barr and Priestley (2004) applies international CAPM model allowing time-varying market segmentation to investigate the global market integration, they find almost 70% of the variation can be explained by world dynamic beta, and the degree of market integration is stable during the period covered by the sample.

Recently, DLY focuses on the entire term structure of interest rates. They use latent factor dynamic Nelson-Siegel model to fit the yield curve. For a set of country yield curves, they fit them by allowing common global factors and idiosyncratic factors. There is interaction between global factors and country-specific factors, and the loading of country-specific factor on global factors is allowed to vary across countries. The finding is global factors explain a big fraction of country yield curve. In this paper I use country-specific factors from the AFDNS model to extract the global yield curve factors. The specification is different with DLY. DLY use two-factors model, while the dynamic Nelson-Siegel model estimation<sup>3</sup> shows that three-factors model significantly improve the goodness-of-fit according to the R-square. Secondly, the level, slope and curvature factors seem to be independent as presented in the macro-finance model of Tam and Yu (2008). CDR manifests the forecasting performance of the independent factors model is no worse than the correlated factors model. Taking

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<sup>3</sup>The OLS estimation of Diebold and Li (2006) model is applied by fixing the  $\lambda$  equal to 0.0600. Results available upon request.



into account above points, we use three-factors model, but assume global level (slope, curvature) factor only depends on the domestic level (slope, curvature) factors. This simplifies the estimation and alleviate the local maximum problem associated with the numerical optimization.

For extracting the common factor, principle component analysis is a popular method. The shortcoming is no economic significance. In this paper, we use Kalman filter to extract global factors, and principle component is an interesting basis for comparison. First, we decompose the country-specific factors:

$$\begin{aligned} l_{it} &= L_t + u_{it}^l \\ s_{it} &= S_t + u_{it}^s \\ c_{it} &= C_t + u_{it}^c \end{aligned} \quad (3)$$

where  $l_{it}$ ,  $s_{it}$ ,  $c_{it}$  are country-specific factors from the independent AFDNS estimation,  $L_t$ ,  $S_t$ ,  $C_t$  are global level, slope and curvature factors. The  $u_{it}^l$ ,  $u_{it}^s$ ,  $u_{it}^c$  are country idiosyncratic level, slope and curvature factors. The  $i$  denotes one of four countries: the US, the UK, Germany and Japan. As aforementioned, the assumption of independent level, slope and curvature dynamics are reasonable, therefore, we extract three global factors independently. we assume country idiosyncratic factors follow an AR(1) process:

$$\begin{pmatrix} l_{1t} - L_t \\ l_{2t} - L_t \\ \vdots \\ l_{kt} - L_t \end{pmatrix} = \begin{pmatrix} \beta_1 & 0 & 0 & 0 \\ 0 & \beta_2 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \beta_k \end{pmatrix} \begin{pmatrix} l_{1t-1} - L_{t-1} \\ l_{2t-1} - L_{t-1} \\ \vdots \\ l_{kt-1} - L_{t-1} \end{pmatrix} + \begin{pmatrix} w_{1t} \\ w_{2t} \\ \vdots \\ w_{kt} \end{pmatrix} \quad (4)$$

$k$  is no. of countries. The specification assumes the country idiosyncratic factors are independent, with the diagonal variance-covariance matrix. This make sense economically if there is no regional factors in the hierachical model. It is more an empirical problem than a theoretical one.

The alternative specification is

$$\begin{pmatrix} l_{1t} - \varphi_1 L_t \\ l_{2t} - \varphi_2 L_t \\ \vdots \\ l_{kt} - \varphi_k L_t \end{pmatrix} = \begin{pmatrix} \beta_1 & 0 & 0 & 0 \\ 0 & \beta_2 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \beta_k \end{pmatrix} \begin{pmatrix} l_{1t-1} - \varphi_1 L_{t-1} \\ l_{2t-1} - \varphi_2 L_{t-1} \\ \vdots \\ l_{kt-1} - \varphi_k L_{t-1} \end{pmatrix} + \begin{pmatrix} w_{1t} \\ w_{2t} \\ \vdots \\ w_{kt} \end{pmatrix}$$

This specification allows different factor loadings of country-specific factors on global factors, while the fit is also an empirical problem, this specification nests the (4) specification. The global factor dynamic is also given by an AR(1) process:

$$L_t = \alpha + \rho L_{t-1} + \epsilon_t \quad (5)$$

if we replace the  $L_t$  and  $l_{it}$  with  $S_t$ ,  $C_t$ , the model can be used to extract the global slope and curvature factors.

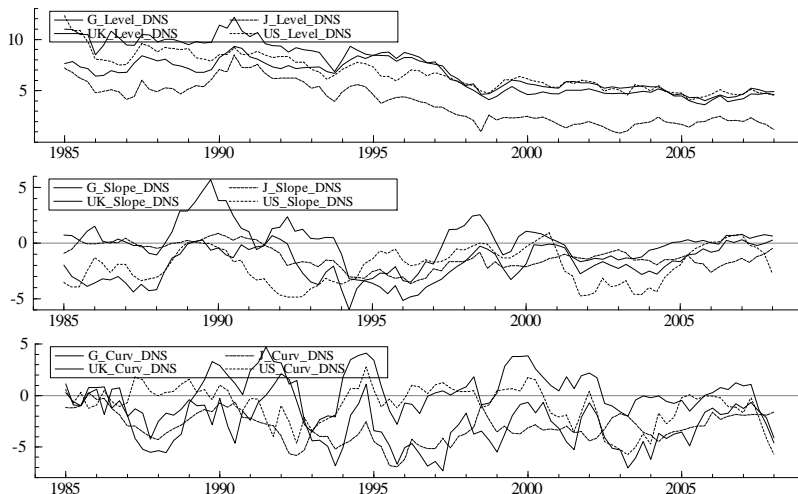


Figure 3: Empirical Level, Slope and Curvature Factors across Countries

### 3.3 Estimates of country-specific and global factors

Non-linear least squares can be employed to estimate the dynamic Nelson-Siegel model. In Diebold and Li (2006), they fix the  $\lambda_t$  and set it equal to value that maximize the loading on the curvature factor at 30 months. In so doing, one can estimate the DNS model by ordinary least squares and make the numerical optimization more reliable. The Kalman filter is an efficient method for estimating the state-space system (1) and (2). The state-space estimation fully exploits the signal extraction information that is not captured by independent OLS estimation. The free  $\lambda_t$  estimates may improve the estimations, but here I fix the  $\lambda_t$  at 0.600 because the estimates are otherwise incomparable when we are extracting out global factors. In practice, free or fixed  $\lambda_t$  is not an issue, I get almost same estimates of latent factors from either method.

The Kalman filter estimation is initialized by unconditional covariance matrix of the state vector and mean vector from the OLS estimates. The starting transition matrix parameters are also from regression of factors extracted by independent OLS estimation. Figure 3 plots the empirical level, slope and curvatures factors across countries.

The summary statistics of factors from Kalman filter estimation is presented in Table 2. We note that the level and slope factors is persistent, while the curvature factor is less persistent in all countries. The augmented Dickey-Fuller (ADF) test show all U.S. factors are stationary, but yield curve factors in other countries are nonstationary with exception of U.K. curvature factors. Although the Pearson and likelihood ratio tests reject the independence of level factor and slope factor, in empirical macro-finance model (Diebold, Rudebusch and Aruoba

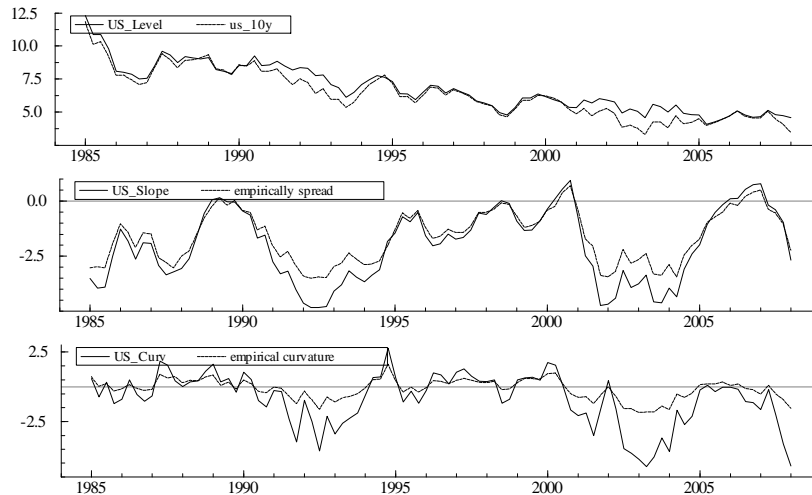


Figure 4: Level, Slope, Curvature Factors and Empirical Correspondents

(2006), Tam and Yu (2008)), one factor contains little extra information about other factors or macro-variables. Diebold and Li (2006) provides the empirical evidence of the interpretation of level, slope and curvature factors as long-term, short-term and medium term factors. In figure 4 I plot the 10-year yield, 3-month yield minus 10-year yield, and two times 2-year yield minus 10-year and 3-month yields with the level, slope and curvature factors for the United States<sup>4</sup>.

Table 2 About Here

The estimation results indicate that the dynamic Nelson-Siegel model fits the yield curve. The DNS model replicates the average upward sloping yield curves of Germany, Japan, the US and the S-shape of the UK. It is important to note that the model fits the middle region of yield curves better than the end regions. This might be a stylized fact of the DNS model, as pointed out in Diebold and Li (2006): ".....because the maturities are not equally spaced, we implicitly weight the most "active" region of the yield curve most heavily when fitting the model".

The Kalman filter estimation of system equation (4) and (5) is applied to extract the global factors of yield curves. The unrestricted vector autoregression (VAR) estimation shows one factor has little extra information about the dynamic of other factor, plus empirical evidence from Diebold and Li (2006), Tam and Yu (2008), therefore we extract the global level, slope and curvature factors by independently iterating the Kalman filter. This simplifies the extraction of

<sup>4</sup>For other countries, the 3-month yield is not available.

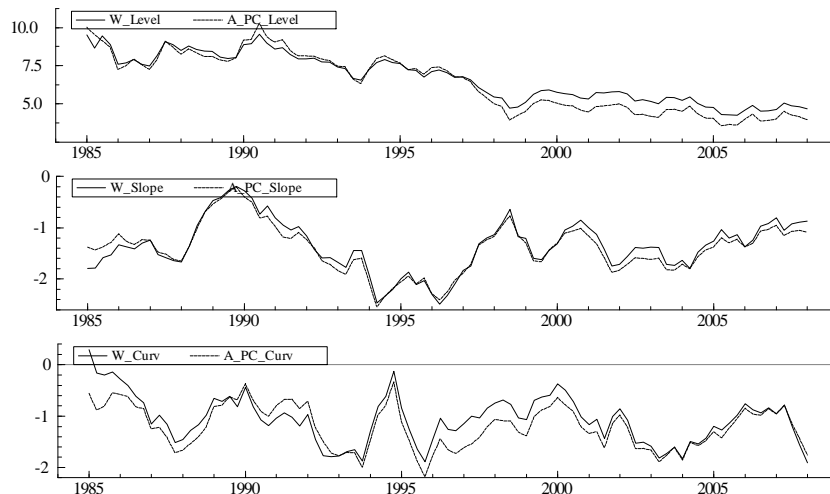


Figure 5: Global Level, Slope and Curvature Factors

global factors significantly. We initialize the Kalman filter with the unconditional covariance matrix and a mean vector from the average of country-specific factors. The estimated parameters are reported in Table 3.

Table 3 About Here

The global factors in essence is a common component of country-specific factors. Two interesting questions before we scrutinize the global factors are: what is the interpretation power of one common component at most? what is the relationship of the component extracted by the Kalman filter and component from principle component analysis? To answer questions, the principle component analysis results are presented in the down panel of Table 5. As we mentioned, the cross-correlation of level factors is higher than slope and curvature factors. The first principle component can explain 91% of variation of the country-specific level factors. For slope and curvature factors, only 50% and 39% of variation can be interpreted by the first principle component. There is strong interactions between global factors from the Kalman filter and the first principle component. The adjusted first principle component and global factors are plotted in the figure 5. The correlations of level, slope and curvature factors and the corresponding first principle components are respectively 0.95, 0.87 and 0.75. The table 6 gives the descriptive statistics of global factors. As in the country model, the level factor is more persistent than the slope and curvature factors.

## 4 Global yield curve and world economic activity

### 4.1 Country-specific yield factors and economic activity

It is well-established that yield factors contain information about the future path of economic activity. Examples have: Bonser-Neal and Morley (1997), Estrella and Hardouvelis (1991), Estrella and Mishkin (1997), Hamilton and Kim (2002), Plosser and Rouwenhors (1994), Rudebusch and Williams (2007), among others.

There are three major conclusions from the previous empirical studies. First, yield spreads and interest rates have enduring power of predicting the real economic growth and inflation, thus these financial variables as a leading indicator are robust. Second, for most OECD countries, the yield slope predicts real growth rate better than predicts nominal growth rate. The exception is UK, that might be induced by the high inflation in late 1980s. The third conclusion is that binary models are more stable than continuous models in most circumstances.

Most of previous studies used the following regression to investigate the predictability of the yield spread for real activity

$$g_{t \rightarrow t+k} = \alpha_0 + \alpha_1 Spread_t + \eta_t$$
$$Spread_t = y_{t(\tau_n)} - y_{t(\tau_1)}$$

Alternatively, we use extracted latent slope and curvature factors for predicting real economic growth:

$$g_{t \rightarrow t+k} = \alpha_0 + \alpha_1 s_t + \alpha_2 c_t + \eta_t$$

This specification is based on the economic interpretation of factors of dynamic Nelson-Siegel (Diebold and Li (2006), Diebold, Rudebusch and Aruoba (2006), Tam and Yu (2008)), figure 4 presents the evidence. The curvature factor may provide extra information in predicting the future real activity.

For predicting the future inflation, the most frequently used specification is

$$\pi_t = \alpha_0 + \alpha_1 Spread_t + \eta_t$$

In our yield curve factors model, the corresponding specification is

$$\pi_t = \alpha_0 + \alpha_1 l_t + \alpha_2 s_t + \eta_t$$

Empirically, the long-term bond should have information about expected inflation according to the rational expectation hypothesis and Fisher equation. Therefore, the level factor that have explanation of long-term factors is employed, in addition, the short-term slope factor is also employed because it stand for the stance of monetary policy.

First of all, I review the forecasting usefulness of yield curves for Germany, U.K., U.S and Japan. Table 5 and Table 6 present the results of regressions

for predicting real growth rates and inflations. There are some points to note about the results. First, the most useful predictor depend on the specific country. For Germany, the medium-term curvature factors has significant predictive power on forecasting. For the United States, it is also the curvature factor predicting the real economic activity. However, for Japan, it is the short-term slope factor has the predictive power. Second, for Germany, Japan and the US, the predictive ability is particularly strong at long horizon. Third, for the UK, yield factors seem have lower power of predictability, only at long horizon it is significant. This finding is consistent with Plosser and Rouwenhorst (1994) who provide further evidence that the yield spread can predict the nominal growth rate significantly. The t-values are calculated using Newey-West (1987) heteroskedasticity and autocorrelation consistent standard errors. That eliminates the effect of moving average due to the overlapping forecasting horizons. This applies to all the following results except the Possion regression results.

Table 5 About Here

The level factor is consistently significant on predicting the inflation rate. The slope factor, as conjectured, contains extra information on the future inflation. The forecasting power is strong for Germany, Japan and the UK, but to a less extent for the US.

Table 6 About Here

Regarding the predictive ability on future inflation, the explanation is usually Fisher decomposition which states that nominal interest rate can be divided into the ex ante real interest rate and the expected inflation. The predictive power of future real activity is thought from the monetary policy and investor expectations. The tightening monetary policy implies a rise in short-term interest rates, typically the long-term interest rates will also rise but usually be less. As a consequence, the yield spread narrows, the polar case is it turn to negative, this is so-called inverted yield curve. If investors expect future economic growth, it means more profitable investment opportunities. In order to take the advantage of opportunities, more bonds are issued, and these bonds are usually long-term for avoiding risk, this increases the bond return. This behavior thus connects the spread with the expected future economic activity.

## 4.2 Out-of-sample forecasting accuracy of yield spread and factors

Recently, the macro-finance model in the framework of (latent) affine term structure provides strong evidence of interactions with macro-variables, such as Ang, Piazzesi and Wei (2006) and Dewachter and Lyrio (2003). Theoretically, the entire term structure should have more information about future economic activities since the slope is a member of the yield curve information set. However, empirically, it is more complicated since the relationship may be nonlinear,

latent factors are possible correlated therefore lead to multicollinearity. Empirically, we need compare the forecasting ability of two models.

Because the world interest rates are not observable, we can't examine the predictive ability of world spread on forecasting the world economic activity. The yield curve model in section 3 provide us a tool for extracting out global factors. It is suitable for the purpose in this paper. However to proof the predictive usefulness of factors from dynamic Nelson-Siegel model, we need compare it with the spread's forecasting performance, since previously most of studies on this strand of literature focus on the spread.

In order to test the predictive power, we should choose actively traded debt securities that incorporate the market's expectations. The government bond is obviously a good choice. But which yield spread? the spread between 10-year and 3-month or 1-year? We choose yield spread according to two empirical criterions. First, availability of yields. Second, in forecast of real activity, the most significant results from two treasury yields whose maturities are far apart. Hence, the spread for the US is the difference between 10-year yield and 3-month yield, for Germany and Japan, 10-year yield and 1-year yield, for the UK, the difference between 10-year yield and 6-month yield.

The out-of-sample forecasting accuracy of the yield spread and yield factors is presented in Table 7. We note that the relative forecasting performance of two models is country-dependent. For Germany, yield factors forecast better. It is consistent with results in Table 5, the empirical correspondent of the yield spread, the slope factor has low interpretation power. For Japan, Both RMSE and MAE criterions support that the yield spread is preferable. For the US, interesting, at short horizon, factors are preferred, at medium horizon, the spread is a better choice. Due to lack of predictive power of both factors and spread on real economic activity, the UK results are skipped. However, the predictive differences with spreads or yield factors are not big. This supports employment of factors for the purpose of examining the relationship between global yield curve and world economic activity.

Table 7 About Here

### 4.3 Global yield factors and economic activity across countries

The predictive usefulness of yield curve is not only well-established in the US but also internationally. Jorion and Mishkin (1991) found strong evidence the term structure have predictive power on future inflation in West Germany, Britain and Switzerland. Plosser and Rouwenhorst (1994) evaluated the information in the term structure about future real economic growth in three industrialized countries. In addition, they found evidence of linkages between real economic growth and yield spreads across countries. Bonser-Neal and Morley (1997) investigated the predictive power of the term structure on real economic activity in 11 industrial countries.

Although there are a lot of international studies on the predictive power of the yield curve, but usually investigate each country independently. Few studies examine the existence of a global yield curve that predicts the world or cross-country economic activity. However this is an interesting exercise. There is increasing international trade, FDI and international asset trade, Kose et al (2003) identified a common world business cycle factor. On the other hand, The financial deregulations may increase the integration degree of financial market, in such case a global yield curve may explain most of variation of yield curves across countries. Diebold, Li and Yue (2007) find that there do exist the global yield curve factors. The main purpose of the paper is to investigate relationship between the global yield curve and world economic activity. Our empirical question is: Does global yield factors predict the economic activity in each country?

Which countries should be investigated? The data availability is the first criterion. The available data should cover a long period, particularly this study is about a low frequency phenomenon, quarterly real growth rate. Second, only countries with well-developed financial markets can be included. Otherwise, the yield spread can't reflect the market expectation. Third, the country should play a significant role in world business cycles. Thus, in this study, I investigate Germany, Japan, the UK and the US cases. The Japanese financial market are restrictive before 1980, but since 1985, the deregulation is completed and markets are liquid and transparent (Zhu 2007).

The global factors are extracted in section 3. These factors are employed to examine the predictive power on real growth rates and inflation across countries. The results are reported in Table 8 and Table 9. There is strong evidence that global yield factors do indeed have information on the economic activity in each countries. R-square is usually lower for the real growth forecasting because although there are common world business cycle factor and global yield curve factors, there are also important idiosyncratic factors, therefore, the forecasting accuracy is not as high as in the model using country-specific factors. For inflations, the results using domestic and global factors are similar, this may indicate that inflations are more synchronized than real economic activity. This is no surprise since the real activity is a much more complicated variable and it subjects to the specific structure of country's macroeconomy.

Table 8 About Here

Table 9 About Here

#### **4.4 Global yield factors and covariance of economic activities**

The predictive power of global yield factors is not fully investigated in the model in above subsection. To get more insight on this issue, we need examine the links between bilateral business cycle correlations and global yield factors. This



make the analysis more robust. The global yield factors should have information beyond those on country-specific factors.

The bilateral correlations are from the conditional dynamic correlation (DCC) analysis based on DCC-GARCH model (Engle 2002). This model is appropriate for the purpose here. It is extensively applied because it preserves the simplicity of univariate model in a multivariate setting. The DCC-GARCH model for factors is as follows:

$$\mathbf{f}_t | \Omega_t \sim N(0, H_t)$$

$$H_t = D_t R_t D_t$$

$\mathbf{f}_t$  is the vector of factors, in this study, real growth rates for aforementioned four countries. The maximum likelihood method can be used to estimate the DCC-GARCH model.

The predictive ability of global factors on selected covariances is presented on Table 10 and Table 11. Like in above subsection, the global level and slope factors are consistently significant in accounting for the six bilateral covariances of inflations across countries. However, the evidence on real growth is weaker. The global level and slope factors are most significant for predicting the covariance of real growths between Germany and Japan. For the covariance between the UK and the US, the level factors is significant. Global factors also predicts the covariance between Germany and the UK.

Table 10 About Here

Table 11 About Here

From the variance-covariance matrix of real growths in section 2, we know that there are two trends in international business cycles. One is between Germany and Japan, the other is between the UK and the US. Although the evidence is not as strong as the inflation case, but global factors do have information about both trends in world business cycles. However it is important to note that there is asymmetric predictive power, global factors forecast covariances between Germany and Japan better. One natural question is: Does this mean that the US is less subject global factors?

## 4.5 Global yield factors and business cycle synchronization

One conclusion from previous studies is that discrete model are more stable than continuous models in predicting the future economic activity. One opinion is that the economy may involve differently within distinct discrete states. Another argument in favor of discrete model is that the discrete model circumvents the spurious accuracy of continuous variables due to the measurement errors.

In this part, I investigate the relationship between global factors and world business synchronization in a discrete model. The economic recession is indexed by 1. This provide a binary index for each country. The synchroniztion is indexed by the sum of binary indexes from four countries. Any single quater of negative year-over-year real GDP growth is defined as a recession. This is the R1 rule in Rudebusch and Williams. They show that this simple and straightforward rule works well, as it matches the NBER recession quaters well.

Table 12 presents the results on synchronization regression. The global slope and curvature factors show predictive power up to 5-quater ahead. This provides further evidence of predictive ability of global yield curve on world business cycles. The result offers extra information on determinants of international business cycles. Most studies on this strand of literature concentrate on relationship between international business cycles and international trade or FDI.

Table 12 About Here

## 4.6 Policy implications

This research has important policy implications. The global financial markets appear to have become an important channel for the international transimission of disturbances. This aspect of global interactions have predictive power on demestic economic activity, both real and nominal. Forecasts are an important component of many economic decisions. Such evidence on the predictive ability of global yield factors would be useful to national policy markers and international institutions. The domestic export industries would benefit from better forecasts of foreign economic activity. Policy makers can know better what is the impact of a foreign supply shock on domestic economic activity through channel of global yield factors.

The results above document that global inflations comovement more closely than real activities. This tendency implies that international trade and common supply shocks, such as oil shock, display significance in explaining global inflations. The different structures of macroeconomy probably play a role in accounting for a less synchronized real activities. Finding out the mechanism of different macroeconomic structures on world business cycles therefore constitutes an interesting and challenging research agenda.

## 5 Concluding remarks

This paper investigates the predictive power of global yield factors on demestic economic activities and international economic activities. I find the evidence of the predictive ability. Specificaly, global yield factors help forecast the real economic growth in countries investigated. In addition, the Possion regression shows that global factors contain information about international business cycle synchronization. Previous studies document the advantages and importance of

discrete models in the robustness of predictive power of yield curve. This finding provide a further evidence but from a perspective of international environment. A significant fraction of covariances of real growths and inflations across countries can be explained by global yield factors. However the results indicate that inflations are more internationally synchronized than the business cycles.

This empirical study extends the existing literature and provides further evidence on global interactions of financial markets and business cycles. The findings has important policy implications. There are also a lot need to be further studied and constitute a future research agenda, such as, why global inflations comovement more closely than real activities. Why there are seemingly two economic growth trends in industrialized countries, one is between the US and the UK, the other is between Germany and Japan.

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Table 1: Summary Statistics for Bond Yields

| Germany           |        |           |          |           |                    |                    |                     |         |
|-------------------|--------|-----------|----------|-----------|--------------------|--------------------|---------------------|---------|
| maturity (months) | Mean   | Std. Dev. | skewness | kurto-sis | $\hat{\rho}_{(1)}$ | $\hat{\rho}_{(4)}$ | $\hat{\rho}_{(10)}$ | ADF     |
| 12                | 4.6839 | 1.9838    | 0.8804   | 2.8347    | 0.9726             | 0.8302             | 0.4741              | -1.2844 |
| 24                | 4.8784 | 1.890     | 0.8263   | 2.8125    | 0.9644             | 0.8106             | 0.4992              | -1.4170 |
| 60                | 5.4304 | 1.6828    | 0.5046   | 2.4525    | 0.9668             | 0.8256             | 0.6261              | -1.3686 |
| 120               | 5.9123 | 1.4887    | 0.1356   | 2.0378    | 0.9721             | 0.8487             | 0.7493              | -1.3637 |
| Japan             |        |           |          |           |                    |                    |                     |         |
| maturity (months) | mean   | Std. Dev. | skewness | kurto-sis | $\hat{\rho}_{(1)}$ | $\hat{\rho}_{(4)}$ | $\hat{\rho}_{(10)}$ | ADF     |
| 6                 | 0.6377 | 0.9320    | 1.8128   | 5.1715    | 0.8747             | 0.5733             | 0.1031              | -3.7950 |
| 12                | 0.7125 | 0.9531    | 1.7267   | 4.8016    | 0.9705             | 0.8606             | 0.6642              | -1.366  |
| 60                | 1.4568 | 1.0944    | 1.3802   | 3.6660    | 0.9562             | 0.8501             | 0.6794              | -1.757  |
| 120               | 2.2116 | 1.1401    | 1.0795   | 2.9977    | 0.9428             | 0.8689             | 0.7915              | -1.405  |
| U.K.              |        |           |          |           |                    |                    |                     |         |
| maturity (months) | mean   | Std. Dev. | skewness | kurto-sis | $\hat{\rho}_{(1)}$ | $\hat{\rho}_{(4)}$ | $\hat{\rho}_{(10)}$ | ADF     |
| 6                 | 7.1611 | 2.9614    | 0.8244   | 2.4724    | 0.9625             | 0.8175             | 0.5736              | -1.6636 |
| 12                | 7.0951 | 2.7796    | 0.7371   | 2.3721    | 0.9637             | 0.8192             | 0.6133              | -1.6068 |
| 60                | 7.1926 | 2.4158    | 0.3167   | 1.7399    | 0.9594             | 0.8606             | 0.7781              | -1.4806 |
| 120               | 7.1836 | 2.3632    | 0.1929   | 1.5188    | 0.9674             | 0.8966             | 0.8242              | -1.450  |
| U.S.              |        |           |          |           |                    |                    |                     |         |
| maturity (months) | mean   | Std. Dev. | skewness | kurto-sis | $\hat{\rho}_{(1)}$ | $\hat{\rho}_{(4)}$ | $\hat{\rho}_{(10)}$ | ADF     |
| 6                 | 4.9666 | 2.0503    | -0.1494  | 2.5227    | 0.9486             | 0.6980             | 0.2441              | -1.3684 |
| 12                | 5.1406 | 2.0632    | -0.0909  | 2.4999    | 0.9439             | 0.7075             | 0.3075              | -1.3497 |
| 60                | 6.0008 | 1.9061    | 0.2592   | 2.6064    | 0.9165             | 0.7173             | 0.6228              | -2.4572 |
| 120               | 6.3751 | 1.8007    | 0.4949   | 2.6518    | 0.9153             | 0.7222             | 0.7342              | -2.692  |

(1)The summary statistics for Japan is based on Bloomberg sample.  
Notes: (2)  $\hat{\rho}_{(\tau)}$  is the autocorrelation coefficient with lag length  $\tau$  periods.  
(3) The lag length of ADF test is selected by BIC.

Table 2: Summary Statistics for Factors Across Countries (AFDNS Estimates)

| Germany |         |          |          |          |                    |                    |                     |         |
|---------|---------|----------|----------|----------|--------------------|--------------------|---------------------|---------|
| factor  | mean    | Std.Dev. | skewness | kurtosis | $\hat{\rho}_{(1)}$ | $\hat{\rho}_{(4)}$ | $\hat{\rho}_{(10)}$ | ADF     |
| level   | 6.4618  | 1.4306   | -0.1304  | 1.8934   | 0.9689             | 0.8076             | 0.7536              | -1.5858 |
| slope   | -1.6631 | 1.6848   | -0.0327  | 2.1199   | 0.9236             | 0.5359             | -0.0926             | -2.3954 |
| curv    | -2.3964 | 1.8087   | 0.4038   | 2.4149   | 0.8502             | 0.3255             | -0.0314             | -2.8127 |
| Japan   |         |          |          |          |                    |                    |                     |         |
| factor  | mean    | Std.Dev. | skewness | kurtosis | $\hat{\rho}_{(1)}$ | $\hat{\rho}_{(4)}$ | $\hat{\rho}_{(10)}$ | ADF     |
| level   | 3.8205  | 1.9294   | 0.3235   | 1.8920   | 0.9555             | 0.8564             | 0.7660              | -1.5636 |
| slope   | -1.2524 | 1.0790   | 0.0215   | 2.2710   | 0.9303             | 0.7370             | 0.4328              | -1.7734 |
| curv    | -3.0991 | 1.4574   | -0.1858  | 2.9174   | 0.8502             | 0.3809             | -0.0481             | -2.7375 |
| U.K.    |         |          |          |          |                    |                    |                     |         |
| factor  | mean    | Std.Dev. | Skewness | Kurtosis | $\hat{\rho}_{(1)}$ | $\hat{\rho}_{(4)}$ | $\hat{\rho}_{(10)}$ | ADF     |
| level   | 7.2865  | 2.4391   | 0.1418   | 1.4383   | 0.9661             | 0.8977             | 0.8287              | -1.4131 |
| slope   | -0.2054 | 2.0048   | 0.0520   | 3.6397   | 0.9192             | 0.5686             | 0.0122              | -2.6400 |
| curv    | -0.1746 | 1.9176   | 0.1697   | 2.9090   | 0.7610             | -0.0160            | 0.3697              | -3.2687 |
| U.S.    |         |          |          |          |                    |                    |                     |         |
| factor  | Mean    | Standard | Skewness | Kurtosis | $\hat{\rho}_{(1)}$ | $\hat{\rho}_{(4)}$ | $\hat{\rho}_{(10)}$ | ADF     |
| level   | 6.7758  | 1.7293   | 0.6281   | 2.8913   | 0.9122             | 0.7063             | 0.7886              | -3.1029 |
| slope   | -2.0068 | 1.6229   | -0.0951  | 1.8357   | 0.9070             | 0.4299             | -0.2599             | -3.3258 |
| curv    | -0.8723 | 1.8641   | -0.8540  | 3.1599   | 0.7956             | 0.4346             | -0.0564             | -3.3837 |

(1) Factors are from DNS estimation.  
Notes: (2)  $\hat{\rho}_{(\tau)}$  is the autocorrelation coefficient with lag length  $\tau$  periods.  
(3) The lag length of ADF test is selected by SIC.

Table 3: Extraction of Global Yield Curve Factors

| Kalman Filter*               |                    |                   |                   |                   |                   |                   |
|------------------------------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|                              | $\hat{\alpha}$     | $\hat{\rho}$      | $\hat{\beta}_1$   | $\hat{\beta}_2$   | $\hat{\beta}_3$   | $\hat{\beta}_4$   |
| level                        | 0.2104<br>(1.01)   | 0.9608<br>(31.77) | 0.6967<br>(8.42)  | 0.9412<br>(27.22) | 0.9199<br>(15.59) | 0.9955<br>(62.97) |
| slope                        | -0.0988<br>(-0.63) | 0.9192<br>(8.74)  | 0.9313<br>(19.26) | 0.9323<br>(27.60) | 0.9250<br>(19.56) | 0.9304<br>(16.59) |
| curv                         | -0.1890<br>(-0.99) | 0.8345<br>(4.90)  | 0.7909<br>(7.71)  | 0.8060<br>(9.91)  | 0.8885<br>(15.60) | 0.9576<br>(30.42) |
| Principle Component Analysis |                    |                   |                   |                   |                   |                   |
| level                        | eigenvalue         |                   | 3.6332            | 0.2135            | 0.1117            | 0.0416            |
|                              | variance Prop.     |                   | 0.9083            | 0.0534            | 0.0279            | 0.0104            |
|                              | cumulative Prop.   |                   | 0.9083            | 0.9617            | 0.9896            | 1.0000            |
| slope                        | eigenvalue         |                   | 1.9899            | 1.0556            | 0.8166            | 0.1379            |
|                              | variance Prop.     |                   | 0.4975            | 0.2639            | 0.2042            | 0.0345            |
|                              | cumulative Prop.   |                   | 0.4975            | 0.7614            | 0.9896            | 1.0000            |
| curv                         | eigenvalue         |                   | 1.5490            | 1.3123            | 0.7064            | 0.4341            |
|                              | variance Prop.     |                   | 0.3872            | 0.3281            | 0.1762            | 0.1085            |
|                              | cumulative Prop.   |                   | 0.3872            | 0.7153            | 0.8915            | 1.0000            |

- Notes: (1)The statistics in the parentheses are t-values.  
(2)The Japan factors used for extracting global factors consist of estimates of two samples from PACAP and Bloomberg.

Table 4: Summary Statistics for Global Factors

|       | mean    | Std.Dev. | skewness | kurtosis | $\hat{\rho}_{(1)}$ | $\hat{\rho}_{(4)}$ | $\hat{\rho}_{(10)}$ | ADF     |
|-------|---------|----------|----------|----------|--------------------|--------------------|---------------------|---------|
| level | 6.6747  | 1.5292   | 0.1255   | 1.6824   | 0.9617             | 0.8567             | 0.8823              | -1.5457 |
| slope | -1.3509 | 0.4950   | 0.0201   | 2.8583   | 0.9164             | 0.5173             | 0.0742              | 2.8583  |
| curv  | -1.0614 | 0.4553   | 0.2233   | 2.8551   | 0.8095             | 0.2098             | -0.1206             | -3.3837 |

Note:  $\hat{\rho}_{(\tau)}$  is the autocorrelation coefficient with lag length  $\tau$  periods



Table 5: Predicting the Year-Over-Year Real Growth Rate  
Using Slope and Curvature Factors

| Germany        |                      |                      |                      |                      |
|----------------|----------------------|----------------------|----------------------|----------------------|
|                | 1 Year               | 2 Year               | 3 Year               | 4 Year               |
| Slope          | -0.0365<br>(-0.5132) | 0.0234<br>(0.3905)   | 0.0402<br>(0.6665)   | 0.0750<br>(1.1465)   |
| Curvature      | 0.1579<br>(3.7185)   | 0.1407<br>(3.9293)   | 0.1088<br>(3.0232)   | 0.0662<br>(1.6956)   |
| R <sup>2</sup> | 0.3476               | 0.4990               | 0.4628               | 0.3624               |
| Japan          |                      |                      |                      |                      |
|                | 1 Year               | 2 Year               | 3 Year               | 4 Year               |
| Slope          | 0.5246<br>(2.7882)   | 0.5872<br>(3.7472)   | 0.6088<br>(4.2023)   | 0.5547<br>(3.5223)   |
| Curvature      | -0.0272<br>(-0.1936) | -0.0272<br>(-0.2333) | -0.0500<br>(-0.4649) | -0.0575<br>(-0.4913) |
| R <sup>2</sup> | 0.2823               | 0.4984               | 0.6374               | 0.5994               |
| U.K.           |                      |                      |                      |                      |
|                | 1 Year               | 2 Year               | 3 Year               | 4 Year               |
| Slope          | -0.0274<br>(-0.3259) | 0.0306<br>(0.3896)   | 0.0812<br>(1.2216)   | 0.1112<br>(2.2067)   |
| Curvature      | 0.0532<br>(0.5877)   | 0.0276<br>(0.3262)   | 0.0217<br>(0.3038)   | 0.0053<br>(0.0980)   |
| R <sup>2</sup> | 0.0374               | 0.0176               | 0.1130               | 0.2973               |
| U.S.           |                      |                      |                      |                      |
|                | 1 Year               | 2 Year               | 3 Year               | 4 Year               |
| Slope          | -0.0058<br>(-0.0933) | 0.0574<br>(1.0277)   | 0.0588<br>(1.0608)   | 0.0659<br>(1.2604)   |
| Curvature      | 0.1316<br>(2.3293)   | 0.1270<br>(2.5170)   | 0.1299<br>(2.5956)   | 0.0869<br>(1.8468)   |
| R <sup>2</sup> | 0.1826               | 0.3478               | 0.4607               | 0.4302               |

Notes: (1) The statistics in the parentheses are t-values.

(2) Newey and West (1987) heteroskedasticity and autocorrelation consistent standard error are used for calculating t-values.

Table 6: Predicting the Year-Over-Year Inflation Rate Using Level and Slope Factors

|                | Germany            | Japan              | U.K.               | U.S.               |
|----------------|--------------------|--------------------|--------------------|--------------------|
| Level          | 0.1949<br>(3.5869) | 0.0691<br>(1.9427) | 0.1562<br>(2.8807) | 0.0989<br>(2.0164) |
| Slope          | 0.2316<br>(1.2343) | 0.1525<br>(2.3730) | 0.1804<br>(2.7926) | 0.0737<br>(1.4194) |
| R <sup>2</sup> | 0.5535             | 0.5019             | 0.4462             | 0.1628             |

Notes: (1) The statistics in the parentheses are t-values.  
(2) Newey and West (1987) heteroskedasticity and autocorrelation consistent standard error are used for calculating t-values.

Table 7 Out-of-Sample 1 to 6-Quater-Ahead Forecasting Accuracy

|      |         | Germany  |          |          |          |          |          |
|------|---------|----------|----------|----------|----------|----------|----------|
|      |         | 1 Quater | 2 Quater | 3 Quater | 4 Quater | 5 Quater | 6 Quater |
| RMSE | factors | 0.4729   | 0.5045   | 0.5299   | 0.5346   | 0.5334   | 0.5248   |
|      | spread  | 0.5089   | 0.5346   | 0.5589   | 0.5621   | 0.5468   | 0.5296   |
| MAE  | factors | 0.4254   | 0.4493   | 0.4660   | 0.4660   | 0.4651   | 0.4617   |
|      | spread  | 0.5620   | 0.5700   | 0.5761   | 0.5811   | 0.5690   | 0.5689   |
|      |         | Japan    |          |          |          |          |          |
| RMSE | factors | 0.7592   | 0.7621   | 0.7763   | 0.7751   | 0.7717   | 0.7556   |
|      | spread  | 0.6504   | 0.6436   | 0.6493   | 0.6397   | 0.6298   | 0.6212   |
| MAE  | factors | 0.6423   | 0.6388   | 0.6596   | 0.6506   | 0.6406   | 0.6224   |
|      | spread  | 0.5562   | 0.5375   | 0.5360   | 0.5187   | 0.5016   | 0.4959   |
|      |         | U.S.     |          |          |          |          |          |
| RMSE | factors | 0.5090   | 0.5312   | 0.5556   | 0.5736   | 0.5707   | 0.5739   |
|      | spread  | 0.5494   | 0.5480   | 0.5477   | 0.5388   | 0.5177   | 0.5046   |
| MAE  | factors | 0.4037   | 0.4190   | 0.4411   | 0.4588   | 0.4459   | 0.4477   |
|      | spread  | 0.4392   | 0.4389   | 0.4500   | 0.4549   | 0.4411   | 0.4399   |

Notes: (1)the factor model uses slope and curvature factors from the yield curve.  
(2) the spread model uses the yield spread between the 10-year yield and the short-term yields, respectively, for Germany and Japan, 1-year yield, for US, 3-month yield.

Table 8: Predicting the Year-Over-Year Real Growth Rate  
Using Global Slope and Curvature Factors

| Germany        |                      |                      |                      |                      |
|----------------|----------------------|----------------------|----------------------|----------------------|
|                | 1 Year               | 2 Year               | 3 Year               | 4 Year               |
| Slope          | 0.5904<br>(2.5450)   | 0.5888<br>(2.4148)   | 0.3994<br>(1.2536)   | 0.1876<br>(0.7354)   |
| Curvature      | 0.6026<br>(2.3557)   | 0.3444<br>(1.2809)   | 0.1570<br>(0.5367)   | -0.1235<br>(-0.4387) |
| R <sup>2</sup> | 0.3643               | 0.3684               | 0.1992               | 0.1368               |
| Japan          |                      |                      |                      |                      |
|                | 1 Year               | 2 Year               | 3 Year               | 4 Year               |
| Slope          | 0.6450<br>(1.3615)   | 0.8421<br>(1.9818)   | 0.8923<br>(2.2186)   | 0.7808<br>(1.9613)   |
| Curvature      | 0.1144<br>(0.2190)   | 0.2130<br>(0.4546)   | 0.0746<br>(0.1682)   | 0.0189<br>(0.0423)   |
| R <sup>2</sup> | 0.1062               | 0.2649               | 0.3409               | 0.5994               |
| U.K.           |                      |                      |                      |                      |
|                | 1 Year               | 2 Year               | 3 Year               | 4 Year               |
| Slope          | 0.1617<br>(1.3615)   | -0.1829<br>(-0.6217) | -0.0071<br>(-0.0267) | 0.2015<br>(0.8959)   |
| Curvature      | -0.4554<br>(-1.5461) | 0.3613<br>(1.1136)   | 0.3998<br>(1.3693)   | 0.2836<br>(1.1434)   |
| R <sup>2</sup> | 0.1617               | 0.0946               | 0.1384               | 0.1866               |
| U.S.           |                      |                      |                      |                      |
|                | 1 Year               | 2 Year               | 3 Year               | 4 Year               |
| Slope          | -0.3464<br>(-1.7313) | -0.1499<br>(-0.8700) | -0.0953<br>(-0.6797) | 0.0597<br>(0.3769)   |
| Curvature      | 0.3910<br>(1.7719)   | 0.6007<br>(3.1614)   | 0.7141<br>(4.6167)   | 0.4039<br>(2.3416)   |
| R <sup>2</sup> | 0.1632               | 0.3058               | 0.5437               | 0.3100               |

Notes: (1) The statistics in the parentheses are t-values.

(2) Newey and West (1987) heteroskedasticity and autocorrelation consistent standard error are used for calculating t-values.

Table 9: Predicting the Year-Over-Year Inflation Rate Using  
Global Level and Slope Factors

|                | Germany | Japan              | U.K.               | U.S.               |
|----------------|---------|--------------------|--------------------|--------------------|
| Level          | N.A.    | 0.2256<br>(4.3886) | 0.3347<br>(5.9508) | 0.1577<br>(4.1138) |
| Slope          | N.A.    | 0.3982<br>(2.5175) | 1.0506<br>(6.0713) | 0.3924<br>(3.3280) |
| R <sup>2</sup> | 0.5535  | 0.5396             | 0.7349             | 0.4813             |

Notes: (1) N.A. : the regression is nonstationary.  
(2) The statistics in the parentheses are t-values.  
(3) Newey and West (1987) heteroskedasticity and autocorrelation consistent standard error are used for calculating t-values.

Table 10: Predicting The Conditional Covariance of Real Growth Rate Across Countries  
Using Global Level, slope and Curvature Factors

| Germany and Japan |                      |                      |                      |                      |                      |                      |
|-------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
|                   | 1 Quater             | 2 Quater             | 3 Quater             | 4 Quater             | 5 Quater             | 6 Quater             |
| Level             | 0.0842<br>(9.6972)   | 0.1316<br>(4.6989)   | 0.1172<br>(4.1283)   | 0.1110<br>(3.3358)   | 0.1111<br>(3.6180)   | 0.1131<br>(3.4330)   |
| Slope             | 0.1557<br>(5.9042)   | 0.3439<br>(4.0402)   | 0.3440<br>(3.9885)   | 0.4117<br>(4.0706)   | 0.3850<br>(4.1270)   | 0.3443<br>(3.4408)   |
| Curv              | -0.1346<br>(-4.4860) | -0.3069<br>(-3.1707) | -0.2106<br>(-2.1471) | -0.3196<br>(-2.7783) | -0.2461<br>(-2.3198) | -0.0968<br>(-0.8508) |
| R <sup>2</sup>    | 0.5772               | 0.3461               | 0.2322               | 0.2325               | 0.2649               | 0.2719               |
| U.K and U.S.      |                      |                      |                      |                      |                      |                      |
|                   | 1 Quater             | 2 Quater             | 3 Quater             | 4 Quater             | 5 Quater             | 6 Quater             |
| Level             | 0.0473<br>(3.2480)   | 0.1479<br>(2.4114)   | 0.0912<br>(1.8793)   | 0.0854<br>(1.7486)   | 0.0950<br>(1.8737)   | 0.0817<br>(1.6667)   |
| Slope             | 0.0453<br>(1.0244)   | 0.3167<br>(1.6991)   | 0.1873<br>(1.2701)   | 0.1819<br>(1.2255)   | 0.2056<br>(1.3341)   | 0.1800<br>(1.2077)   |
| Curv              | -0.0542<br>(-1.0785) | -0.1885<br>(0.2120)  | -0.1136<br>(-0.6776) | -0.1087<br>(-0.6437) | -0.1520<br>(-0.8673) | -0.1592<br>(-0.9392) |
| R <sup>2</sup>    | 0.2772               | 0.1356               | 0.1049               | 0.1130               | 0.1359               | 0.1199               |
| Germany and U.K.  |                      |                      |                      |                      |                      |                      |
|                   | 1 Quater             | 2 Quater             | 3 Quater             | 4 Quater             | 5 Quater             | 6 Quater             |
| Level             | 0.0288<br>(2.3557)   | -0.0100<br>(-0.3293) | -0.0736<br>(-2.3860) | -0.0752<br>(-2.1475) | -0.0887<br>(-1.9672) | -0.0889<br>(-2.0549) |
| Slope             | -0.0577<br>(-1.5517) | -0.1494<br>(-1.6184) | -0.2107<br>(-2.2465) | -0.2420<br>(-2.2758) | -0.2467<br>(-1.8004) | -0.2118<br>(-1.6118) |
| Curv              | -0.0433<br>(-1.0237) | -0.0500<br>(-0.4758) | 0.0725<br>(0.6800)   | 0.0579<br>(0.4792)   | 0.0515<br>(0.3305)   | 0.0157<br>(0.1053)   |
| R <sup>2</sup>    | 0.1548               | 0.0467               | 0.1311               | 0.1601               | 0.1592               | 0.1768               |

Notes: (1) The statistics in the parentheses are t-values.  
(2) Newey and West (1987) heteroskedasticity and autocorrelation consistent standard error are used for calculating t-values.

Table 11: Predicting The Conditional Covariance of Inflation Rate Across Countries  
Using Global Level, Slope and Curvature Factors

|                | G and J              | G and U.K.           | G and .US.          | J and. U.K.        | J and U.S.           | U.K. and U.S.        |
|----------------|----------------------|----------------------|---------------------|--------------------|----------------------|----------------------|
| Level          | 0.0932<br>(2.2289)   | 0.7744<br>(2.4088)   | 0.0336<br>(2.8868)  | 0.2661<br>(4.1737) | 0.1124<br>(4.2492)   | 0.1763<br>(4.4587)   |
| Slope          | 0.1458<br>(1.1475)   | 0.2794<br>(2.7678)   | 0.1256<br>(3.5529)  | 0.7943<br>(4.0996) | 0.3076<br>(3.8282)   | 0.5329<br>(4.4344)   |
| Curv           | -0.2132<br>(-1.4753) | -0.0015<br>(-0.0137) | -0.0232<br>(0.0402) | 0.0211<br>(0.0957) | -0.0849<br>(-0.9288) | -0.0905<br>(-0.6623) |
| R <sup>2</sup> | 0.2820               | 0.3480               | 0.2631              | 0.5498             | 0.4632               | 0.5034               |

Notes: (1) The statistics in the parentheses are t-values.

(2) G: Germany, J: Japan;

Table 12: Predicting World Recession Synchronization Using Global  
Slope and Curvature Factors in a Possion Regression

|           | 1 Quater           | 2 Quater           | 3 Quater           | 4 Quater           |
|-----------|--------------------|--------------------|--------------------|--------------------|
| Slope     | 0.6084<br>(2.09)   | 0.7189<br>(2.24)   | 1.2125<br>(3.20)   | 1.3109<br>(3.37)   |
| Curvature | -0.6553<br>(-1.85) | -0.8515<br>(-2.18) | -1.6648<br>(-3.57) | -1.5456<br>(-3.17) |
|           | 5 Quater           | 6 Quater           | 7 Quater           | 8 Quater           |
| Slope     | 1.1275<br>(2.91)   | 0.6654<br>(1.74)   | 0.4341<br>(1.10)   | 0.4272<br>(1.03)   |
| Curvature | -1.3728<br>(-2.86) | -0.6900<br>(-1.47) | -0.6487<br>(-1.38) | -0.6596<br>(-1.33) |

Notes: (1) The statistics in the parentheses are t-values.

(2) 4-quater lagged slope factor and 2-quater lagged  
curvature factor are applied